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Four Essays of Environmental Risk-Mitigation

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FOUR ESSAYS OF ENVIRONMENTAL RISK-MITIGATION

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by

Chiradip Chatterjee

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To: Dean Kenneth G. Furton
College of Arts and Sciences

This dissertation, written by Chiradip Chatterjee, and entitled Four Essays of Environmental Risk-Mitigation, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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I dedicate my thesis to my parents, my sister, and my wife. Without their love and support, I would not be able to come this far.

ABSTRACT OF THE DISSERTATION

FOUR ESSAYS OF ENVIRONMENTAL RISK-MITIGATION

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Expected damages of environmental risks depend both on their intensities and probabilities. There is very little control over probabilities of climate related disasters such as hurricanes. Therefore, researchers of social science are interested identifying preparation and mitigation measures that build human resilience to disasters and avoid serious loss. Conversely, environmental degradation, which is a process through which the natural environment is compromised in some way, has been accelerated by human activities. As scientists are finding effective ways on how to prevent and reduce pollution, the society often fails to adopt these effective preventive methods. Researchers of psychological and contextual characterization offer specific lessons for policy interventions that encourage human efforts to reduce pollution. This dissertation addresses four discussions of effective policy regimes encouraging pro-environmental preference in consumption and production, and promoting risk mitigation behavior in the face of natural hazards.

The first essay describes how the speed of adoption of environment friendly technologies is driven largely by consumers' preferences and their learning dynamics rather than producers' choice.

The second essay is an empirical analysis of a choice experiment to understand preferences for energy efficient investments. The empirical analysis suggests that subjects tend to increase energy efficient investment when they pay a pollution tax proportional to the total expenditure on energy consumption. However, investments in energy efficiency seem to be crowded out when subjects have the option to buy health insurance to cover pollution related health risks.

In context of hurricane risk mitigation and in evidence of recently adopted My Safe Florida Home (MSFH) program by the State of Florida, the third essay shows that households with home insurance, prior experience with damages, and with a higher sense of vulnerability to be affected by hurricanes are more likely to allow home inspection to seek mitigation information.

The fourth essay evaluates the impact of utility disruption on household wellbeing based on the responses of a household-level phone survey in the wake of hurricane Wilma. Findings highlight the need for significant investment to enhance the capacity of rapid utility restoration after a hurricane event in the context of South Florida.

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LIST OF ACRONYMS AND ABBREVIATIONS

IGT	Increase in Green Tax (Treatment)
DGT	Decrease in Green Tax (Treatment)
GHP	Geothermal Heat Pump
RWT	Residential Wind Turbine
RSES	Residential Solar Energy System
EEL	Energy Efficient Lighting
ECB	Energy Conservation Behavior and Energy Efficient Appliances
ESC	Energy Saving Choices
ESC^{LT}	Long Term Energy Saving Choices
ESC^{ST}	Short Term Energy Saving Choices
HI	Health Insurance
MOD	Monitor Others' Decision
Ins1	HI of '$1,000 premium and 35% co-pay with a $20,000 cap'
Ins2	HI of '$1,300 premium and 10% co-pay with a $5,000 cap'
DFS	Department of Financial Services
VFF	Volunteer Florida Foundation
MSFH	My Safe Florida Home
HRMS	Hurricane Risk Mitigation Status
RUM	Random Utility Model

CHAPTER I:

ADOPTION OF GREEN TECHNOLOGY: THE DIFFUSION AND LEARNING PROCESS OF THE CONSUMERS

1. INTRODUCTION

Eco-friendly or green technologies are instrumental in reducing damages to the environment. Yet a significant amount of literature indicates that adoption of eco-friendly technologies can be very slow in absence of economic incentives (Mahajan et al. 1990; Baker 2001; Hartmann 2006). The rationales are twofold. Firstly, firms may not realize the entire social benefit of green technologies (Porter and Kramer 2006; Bessen and Maskin 2009) or may find adoption of environment friendly technologies is not cost-effective (York and Venkataraman 2010; Gang and Abetti 2010). Secondly, path dependence and long equipment replacement cycles of firms can slow down the adoption of eco-friendly technologies in production (Bollinger 2010; Omer 2009).

Adoption of eco-friendly technologies often reduces environmental footprint of products, but may not necessarily change their consumption experience. Energy, for example, can be produced from renewable (e.g., wind mills) and non-renewable (e.g., coal fired power plants) sources. The non-renewable sources of energy, such as coal, are limited and can be exhausted. The renewable sources of energy, such as the sun, wind, geothermal, ocean energy, are available in abundant quantity. Non-renewable sources release emissions in the air when burnt and contribute to global warming, which may cause major environmental and health hazards. While there is not much changes in the consumption experience of energy based on source, renewable and non-renewable energy are substantially different in terms of their environmental impacts.

As energy-generating facilities decide their production process, they may continue using non-renewable (which is cheap and easy to use) sources or set up a renewable energy plant that has quite steep initial costs. Market price of renewable energy is comparatively higher than price of non-renewable energy due to the high initial set-up cost of renewable energy plants. Therefore, is it profitable replacing non-renewable electrical sources with renewable sources for an incumbent electrical facility? Consumer's preference can answer this question.

Firms believe that improvisation needs to be adopted, if appropriate to consumers' experience (Jacob et al. 2009). If dissatisfied, people substitute their consumption instead of spending time to submit a complaint or compromise their preference (Hippel 1986; Jaeger et al. 2003; Nagamachi 1995). Buyers' discretion is very important in success of new technologies, such as renewable sources of energy. For example, the analysts say that Germans are willing to pay for renewable energy out of their concern for the environment and climate change (Bonono et al. 2008). And the rapid switch to renewable energy sources has increased annual electricity bill of German households' by nearly 47%. The significant market demand in Germany for renewable energy, from the environmental and climate change concern, substitutes non-renewable energy sources with renewable energy sources irrespective of a high switching cost. However, the potential of markets for "green" electricity may be limited and other support schemes may be required as there is insufficient market demand (Ek 2005).

With a preference for environmental safety, consumers judge the quality of their consumption choices along their environmental attributes (Chen 2001; Valentini 2009). While producers bring their environmental attributes in production and in advertising (Laroche 2001; Jaffe et al. 2002; Kirchhoff 2000), consumers are unable to readily observe these characteristics. Consumers are also characterized by myopia, habit formation and path dependency (van den Bergh 2010). Adoption of underlying eco-friendly technologies becomes easier, as consumers learn about the environmental benefit claimed by producers.

Let us suppose that a firm can produce X with either of technology x and technology y. While x is the incumbent technology, adoption of y does not improve consumption experience of X. However, y is environmentally benign production technique and X is characterized as G with additional environmental benefit with this underlying method of production. X and G have same consumption purpose and experience, but different in environmental impact. Adoption policies of y fall in four classes: a) increase in environmental awareness, b) help understand qualitative value of the green technologies, c) financial incentives to producers on adoption of eco-friendly technologies and d) set environmental regulations.

Environmental preferences increase with awareness (Coad et al. 2009; Gilg et al. 2005; Mostafa et al. 2007). Literature suggests that publishing "green consumer guides" that adds to environmental awareness can reduce environmental cost of consumption (Chen 2001). Salient environmental benefit of credence goods is difficult to judge and may hold the buyers back in deciding pro-environmental consumption. A third-party intervention is often advised certifying environmental quality of products. Such certifications not only reinforce consumers' value (Cason and Gangadharan 2002; Amacher 2004; Swallow and Sedjo 2000; Dosi and Moretto 2001), but also restrain producers from frequently using cheap-talks claiming their products to be environment friendly. Demonstration also helps consumers understand environmental attribute of products through diffusion of information (Bollinger 2010), as people make consumption choices and expect equivalent utility (Bala and Goyal 1998; Bala and Goyal 2001). As other options become less effective, environmental regulations, financial incentives, or penalties, are most upfront strategies used in promotion of eco-friendly technologies (Stechow et al. 2011; Kelly and Kolstad 1999).

Adoption policies are often interdependent. For example, Cantono and Silverberg (2009) have developed a network model of consumers that describes a reservation price for eco-friendly commodities, which increases with number of buyers. The reservation price is the highest price a buyer agrees to pay. They explain a subsidy policy that initiates a self-sustained process of consumption diffusion, through an initial pool of consumers. Tarui and Polasky (2005) compared rules of discretion in adoption of green technologies and concluded that rules are superior to discretion because discretionary policy gives the firm an incentive to distort investment in order to influence future regulation when there is little uncertainty.

However, there is no common framework that pulls all different policies together. Here I have explained adoption of green technology with consumers' discretion. The framework also describes a process where economic agents, instead of the social planner, make decisions (Kelly and Kolstad 1999). According to Kelly and Kolstad, as people make choices to adopt green technologies, it solves the issue of asymmetric information between consumers and producers. Learning also depends on arrival of information, as agents have some control over the arrival rate of information in active learning.

The rest of the chapter follows the following layout. Section 2 analyzes the choice of technology switch with consumers' discretion. Section 3 explains the criterion of switching technology. Section 4 examines the distribution of Markov time, required time to adopt green technology. Section 5 discusses how policy can reduce the required time to adopt environment friendly technology. Section 6 concludes with implications of our findings and makes suggestions for future research.

2. ADOPTION MODEL

Consumption

Let us suppose that *X* is an infinitely divisible commodity and its environmental quality is q. As *X* is the incumbent commodity, the buyers know the quality q. Here I assume that individuals are identical and they live infinite periods of time and have countless number of consumption choices. However, the marginal utility of spending a dollar on any good or service other than *X* is one. While a consumer consumes x_q units of *X*, the perceived utility (*U*) of the consumer is represented as follows.

$$U = q^{\theta} x_q^{1-\theta} \text{ , where } 0 < \theta < 1 \tag{1}$$

T Consumers have preferences for environmental attributes of their consumption. Let the price of *X* is P_q. We therefore can represent the consumer surplus as,

$$CS^q = q^{\theta} x_q^{1-\theta} - P_q x_q \tag{2}$$

The optimal consumption decision that maximizes consumer surplus is

$$x_q = q \left(\frac{1-\theta}{P_q}\right)^{\frac{1}{\theta}} \tag{3}$$

Therefore, the consumption of *X* is proportional to its environmental quality and decreases with price. Using equation (2), the consumer surplus can be expressed as,

$$CS^q = Aq\left(P_q\right)^{\frac{\theta-1}{\theta}} \tag{4}$$

Here, $A = (1-\theta)^{\frac{1-\theta}{\theta}} - (1-\theta)^{\frac{1}{\theta}}$.

Adoption Criterion

Let the producer needs to bear a sunk-cost K_e ($K_e > 0$) in order to adopt the green technology *y*. As the producer starts produce *X* with technology *y*, the product is classified as *G* with the additional environmental attributes. Quality of *G* is g' and $g' > q$. In order to recover the sunk-cost of technology switch, let the minimum price for *G* is P_g, $P_g = P_q + \varepsilon$ and $\varepsilon > 0$. Suppose there are *N* identical consumers and the discounted present value of increase in total revenue from production of *G* is R^{ε}. Therefore,

$$R^{\varepsilon} = {N\varepsilon x_g}\Big/{(1-\beta)} = {N\varepsilon g'\left(\frac{1-\theta}{P_g}\right)^{\frac{1}{\theta}}}\Big/{(1-\beta)} \tag{5}$$

The discount rate on future returns is β and the optimal consumption of the representative consumer is x_g.

Perceived Quality

The perceived environmental quality of a product depends on consumers' preference for the environmental attributes in it. Hence, the realized (g) and effective (g') environmental quality of *G* can be distinguished.

$$g = \lambda(g')^{b} \tag{6}$$

In the above equation λ represents individuals' preference for environmental attributes of their consumption.[1] I consider no forgetting of information; a consumer does not change his/her opinion once he/she believes that *G* is better alternative than *X*.[2] The fraction of population, who are in favor of *G* is *b*. Therefore, realized (g) environmental quality of *G* increases as more people recognize *G* is a better alternative to *X*.

Quality Threshold

As there is sufficient market demand for *G*, production of *X* stops and the producer adopts *y*. Hence, the consumer surplus from *G* (CS^g) satisfies the condition: $CS^g > CS^q$. It is decomposed to the condition

$$g \geq q\left(\frac{P_g}{P_q}\right)^{\frac{1-\theta}{\theta}} \tag{7}$$

However, the buyers are unable to judge the quality of G until the production starts and the environmental impact of the eco-friendly production technology becomes visible (Cason and Gangadharan 2002).

3. CHOICE OF TECHNOLOGY

Consumers are limited to two choices: a) continue consuming *X* or b) demand for *G*. The buyers do not rely on firms (Cason and Gangadharan 2002). They suspect that the producer of *X* may claim adoption of *y* and earn supernormal profit. Hence, it may be revealed that the quality of *G* is *q*. In accordance, I assume that as the consumers continue the consumption of *X,* the value of *g* is drawn from a normal distribution with mean *q* and

[1] Please see Chatterjee and Eliashberg (1990) and Narayan et al. (2011) for further details and explanation.

[2] Results hardly differ as buyers change their preference from *G* to *X*.

variance σ^2. They recognize the value of g with a distribution $F(g)$ and density $f(g)$. Every period, they observe a signal z. The signal has conditional density $\hbar(z/g)$ and distribution $H(z/g)$. That is, the signals depend on the unknown and true value of g' and variance σ_z^2. Therefore, using the one-step-ahead Bayes map, the transition from $F(g)$ to $F'(g)$ is subject to corresponding signal obtained.

$$f^{'}(g) = \frac{\hbar(z/g)f(g)}{\int_{g\in G}\hbar(z/g)f(g)} \tag{8}$$

Now, let us assume the mean of received signals until period t is $\overline{z_t}$. Following the standard formula (DeGroot 1970), the posterior belief of the representative consumer is normally distributed with mean and variance respectively as,

$$\overline{g_t} = \frac{t\sigma^2\overline{z_t}+q\sigma_z^2}{t\sigma^2+\sigma_z^2} \tag{9}$$

and

$$\sigma_{g,t}^2 = \frac{\sigma^2\sigma_z^2}{t\sigma^2+\sigma_z^2} \tag{10}$$

Mapping the mean and variance for the next period can reproduce the transition of belief. Receiving the signal on $(t+1)^{th}$ period, z_{t+1}, the consumer reviews his belief. Updated belief of the consumer is reflected exploiting the posterior mean ($\overline{g_{t+1}}$) and variance ($\sigma_{g,t+1}^2$).

$$\overline{g_{t+1}} = \frac{z_{t+1}\sigma_{g,t}^2+\overline{g_t}\sigma_z^2}{\sigma_{g,t}^2+\sigma_z^2} \tag{11}$$

and

$$\sigma_{g,t+1}^2 = \frac{\sigma_{g,t}^2\sigma_z^2}{\sigma_{g,t}^2+\sigma_z^2} \tag{12}$$

The pair $\{\overline{g_t}, t\}$ is sufficient statistic of belief F_t. The ultimate goal of the representative consumer is to maximize the discounted present value of expected future returns, or discounted present value of consumer surplus. The effect of these two deciding and opposite forces that determine the choice to switch are twofold. A) Uncertainty leads to an inferior expected consumer surplus on adoption of $\overline{g_t}$. Hence, as the uncertainty reduces over time (the posterior variance of belief decreases with time) with repeated signals, the expected return from switching starts improving. B) As the consumers wait for additional signals, current benefit from adoption of *G* is lost.

The dynamics of the above two opposite forces, resolves the decision of the representative consumer. Using equation (10),

$$\frac{\delta\sigma_{g,t}^2}{\delta t} < 0 \text{ and } \frac{\delta\left(\sigma_{g,t}^2\right)^2}{\delta^2 t} > 0 \tag{13}$$

That is, the uncertainty of the value of g reduces at a decreasing rate over time. By the law of iterated expectation, expected quality of G does not change in subsequent periods. Return from waiting one additional period, therefore, is positive, and reduces over time as uncertainty reduces.

Let the representative consumer's belief at period *t* is normally distributed with mean $\overline{g_t}$ and variance $\sigma_{g,t}^2$. Therefore, probability of $g = q$ on period is,

$$p(\overline{g_t}, t) = \frac{1}{\sqrt{2\pi\sigma_{g,t}^2}} e^{-\frac{(q-\overline{g_t})^2}{2\sigma_{g,t}^2}} \tag{14}$$

By each period, loss in consumer surplus due to increase in price (P_q to P_g) without any increase in quality (q) of consumption is,

$$\left[Aq(P_q)^{\frac{\theta-1}{\theta}} - Ag(P_g)^{\frac{\theta-1}{\theta}}\right] \tag{15}$$

Therefore, the discounted present value of loss (L) in consumer surplus throughout the lifetime is,

$$L = \frac{1}{(1-\beta)}\left[Aq(P_q)^{\frac{\theta-1}{\theta}} - Ag(P_g)^{\frac{\theta-1}{\theta}}\right] \tag{16}$$

Therefore, discounted present value of expected loss in consumer surplus due to false claim of green technology transfer by the producer and consumers' approval to the claim at period t can be derived, multiplying equation (14) and (16).

$$E_t(L) = \frac{p(\overline{g_t},t)}{(1-\beta)}\left[Aq(P_q)^{\frac{\theta-1}{\theta}} - Ag(P_g)^{\frac{\theta-1}{\theta}}\right] \tag{17}$$

The value-function of an individual consuming can be expressed as follows.

$$V(q, F_t) = max\left[Aq(P_q)^{\frac{\theta-1}{\theta}} + \beta V(q, F_{t+1}), \frac{A}{(1-\beta)}\overline{g_t}(P_g)^{\frac{\theta-1}{\theta}} - E_t(L)\right] \tag{18}$$

The above Bellman equation considers that a consumer's choice to stick to X or switch to G, is aimed at optimizing the present discounted value of future returns.

As explained before, the option value from waiting decreases with higher precision as uncertainty reduces over time. That is, the risk of a wrong prediction decreases with increase in number of signals. Exploiting the Bellman equation, any consumers' decision to prefer G to X meets the following condition.

$$\frac{A}{(1-\beta)}\overline{g_t}(P_g)^{\frac{\theta-1}{\theta}} - E_t(L) \geq Aq(P_q)^{\frac{\theta-1}{\theta}} + \beta V(q, F_{t+1}) \tag{19}$$

Let the minimum value of $\overline{g_t}$, that satisfies the condition, is g_t^*. Therefore,

$$\frac{A}{(1-\beta)}g_t^*(P_g)^{\frac{\theta-1}{\theta}} - E_t(L) = Aq(P_q)^{\frac{\theta-1}{\theta}} + \beta V(q, F_{t+1}) \tag{20}$$

The g_t^* is the critical value of posterior mean or the mean value of a consumer's belief that makes the consumers prefer *G* over *X* and wait for no additional signals.

4. MARKOV TIME DISTRIBUTION

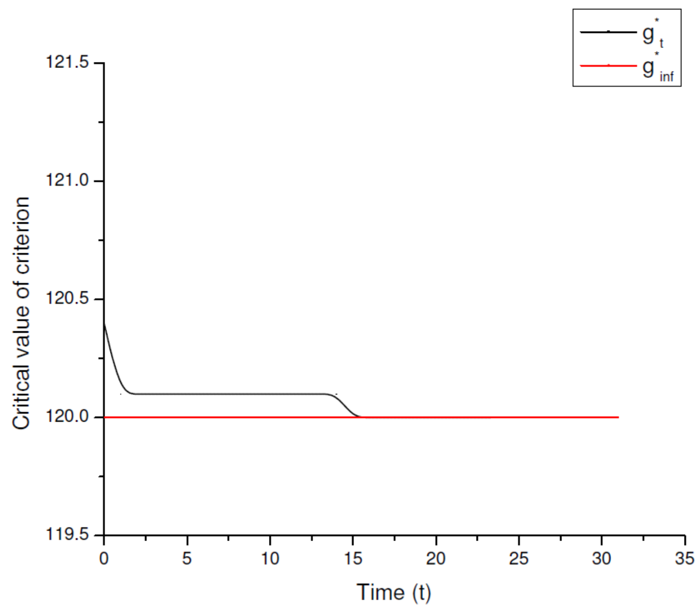
In order to analyze the time and the probability of green technology adoption through the choice of consumers', I calculated the distribution of the Markov time. The Markov time, T, can be explained in the following equation.

$$T = minimum\{t: \overline{g_t} \geq g_t^*\} \tag{21}$$

To illustrate, Markov time is the minimum time required to convince a consumer that *G* is a better than *X*.

The following is an example that will eventually be used to provide numerical comparisons of policies to encourage adoption of *G*. Let $\theta = 0.5$, $q = 100$ and $P_q = 1$. Using equation (3) and (4), $A = 0.25$ and $x_q = 25$. Also, let true quality of *y* (g') is 144 and the discount rate on future returns (β) is 0.95. The cost of technology transfer (K_e) is 10,000. The number of consumers (*N*) is assumed 100. Hence, in order to compensate the cost of technology switch, increase in vending price (ε) is 0.2. Therefore, $P_g = 1.2$. Standard errors of initial belief (σ) and signals received (σ_z) are both 10.

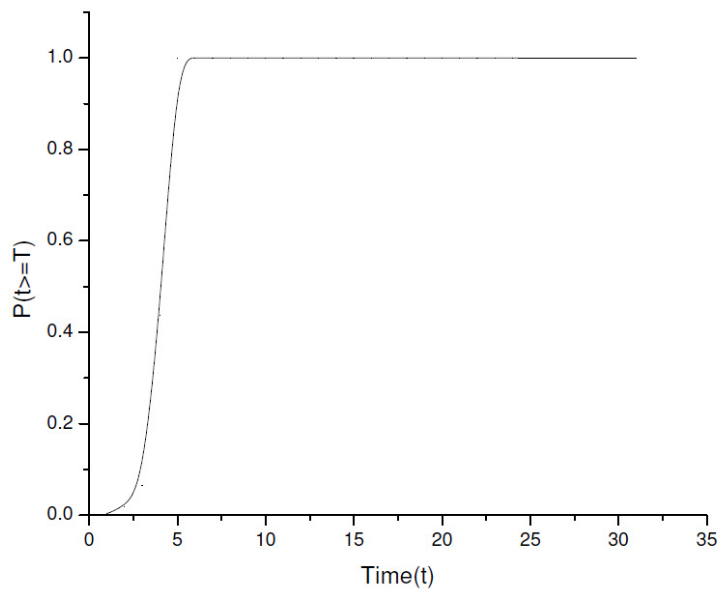
Figure 1: Evolution of critical value of posterior mean over time



$$q = 100, \sigma = 10, \sigma_z = 10, A = 0.25, P_q = 1, P_g = 1.2$$

Uncertainty, over environmental attributes, reduces with increase in number of signals consumer receives. Therefore, as $t \to \infty$, uncertainty of the quality of *G* disappears. When return from environmental attribute is certain ($\sigma^2_{g,t} = 0$), the critical value of posterior mean (g^*_{inf}) is 120, by equation (7). The value of g^*_∞ is the asymptotic critical value of posterior mean. However, the uncertainty keeps the critical value of posterior mean (g^*_t) over the asymptotic limit. The g^*_t can be approximated by estimating the stopping rule illustrated in equation (20). Figure 1 provides a comparison of g^*_t and g^*_{inf}. As uncertainty diminishes with signals, g^*_t tends to its asymptotic limit. The numerical approximation of g^*_t is described in the appendix A.1.

Figure 2: Probability distribution of Markov time



$$q = 100, g' = 144, \lambda = 114, b = 0, \sigma = 10, \sigma_z = 10, A = 0.25, P_q = 1, P_g = 1.2$$

The first passage problem (illustrate it) and probability distribution of Markov time, itself, is an exciting subject of statistical research. Several researchers have estimated distribution of Markov with numerical measure and usually consider that z_t and $\overline{g_t}$ can only take certain discrete values (Ardia 2009; Strigul et al. 2012). Assuming that the signals follow normal distribution with mean g and variance σ_z^2, I have described the approximation process of the probability distribution of Markov time $P(t \geq T)$ in appendix A.2. Figure 2 plots the $P(t \geq T)$ over time. As the probability reaches one, it indicates adoption of *G* by the entire population.

5. POLICY DISCUSSION

The consumers may prefer G to X for individual or social reasons. Therefore, policies may target either individual wellbeing or aggregate social benefit, or both. Following are different aspects that affect the adoption-probability of G and the underlying green technology (y).

Awareness

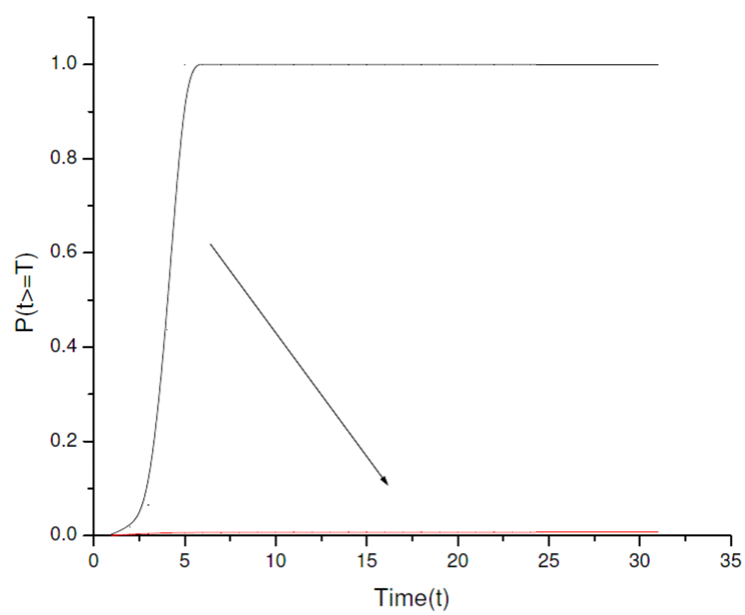
Consumers are different in preference for environmental quality (Luechinger 2009; Lo and Spash 2012), so as their willingness to pay for environmental attributes in consumption. As people may undervalue the importance of the environment, studies often recommend decision of a 'social planner' (Selden and Song 1995; McConnell 1997) to avoid suboptimal social welfare. While buyers are entitled to make their own choices, decisions of a social planner cannot be imposed or are limited in application. It is therefore important and practical to encourage pro-environmental concern of people.

Plastic, for example, is always a concern for the environment. The usage of plastic bags has reached the scale by trillions. The Guinness Book of World Records (2010) has named plastic bag 'the most ubiquitous consumer product'. Market price of plastic bags fails to reflect its true cost to society. Single-use plastic bags adversely affect the fishing, shipping and tourism industries, and cost developing and industrialized nations up to $1.3 billion annually. State agencies in California spend around $25 million to clean up single-use plastic bags. Recycling and managing used plastic bags always put enormous amount of stress on waste management in India (Talyan et al. 2008). Irrespective of several attempts to ban plastic bags, massive market demand encourages its illegal manufacturing and supply. S Shivappa, Chairman of health committee Bangalore City Corporation

(BCC), was quoted saying "Mass awareness is a must, so we have decided to educate them through newspapers and pamphlets" in Times of India on 28th June 2001. The awareness agenda S Shivappa mentioned was for citizens of Bangalore, as BCC was planning to outlaw use of plastic bags less wide than 20 microns. Such evidences establish the importance of consumers' awareness encouraging environment friendly practices.

Following equation (6), decrease in environmental concern can be reflected through decrease in the value of λ. As plotted in Figure (3), adoption of G is never possible when value of λ decreases to 110. As $P(t \geq T)$ never reaches one, it reflects that everyone do not believe in adoption of G. Therefore, even a better innovation of technology fails to successfully replace its substandard substitute as a result of lack of sufficient concern for the environment.

Figure 3: Probability distribution of Markov time as 'Concern' decreases



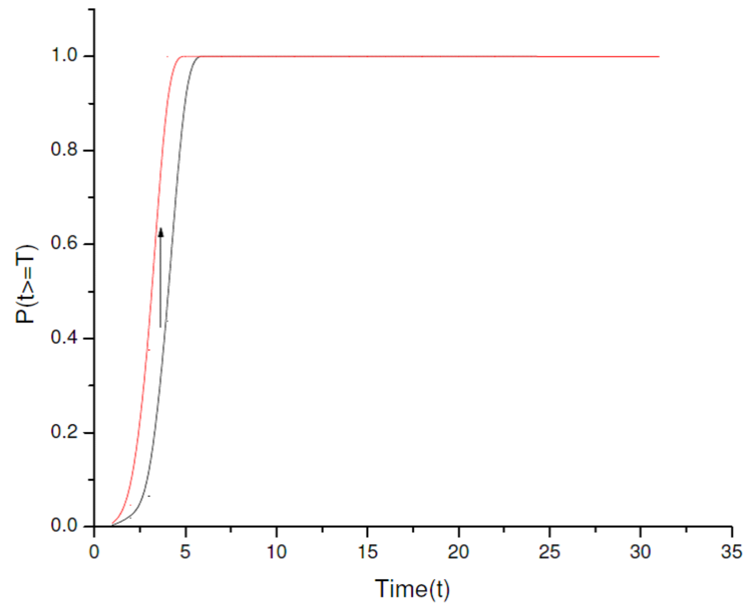
$q = 100, g' = 144, \lambda(\downarrow) = 114 \; to \; 110, b = 0, \sigma = 10, \sigma_z = 10, A = 0.25, P_q = 1, P_g = 1.2$

Banning vs. Penalizing

Adoption of G is not always the optimal decision of consumers with preference for private gain. Also, as learning g' may take too long, environment policies often set rules to ensure adoption of green technologies. Rules can be as rigorous as banning or penalizing non-environment friendly products and technologies. Banning is not always feasible due to social restraints. Setting rules and regulations involves significant administrative concern. Bureaucrats may face severe public protest, while setting and enforcing rules. Rules and regulation may also be introduced to collect bribes (Shleifer and Vishny 1993). Preventing marketing of a regular consumer products, also involves problem of black marketing. Charles W. Schmidt (2004) has cited several examples of illegal transactions related to environmental issues ranging from illegal trading of chlorofluorocarbons (CFCs) to logging. Therefore, legal restriction on consumption of X may not be feasible as long as it has sufficient market demand.

Pollution taxes, such as 'Carbon Tax', can be referred in this context (Mathieu et al. 2012). Carbon tax increases cost of production with emission. Hence, emission reducing production technologies get adopted sooner than before. Let the pollution tax increases the price of X by 10% (from 1 to 1.1). If so, the relative price of G decreases. In other words, it costs consumers less to change their consumption habit. Hence, adoption of y becomes faster. Figure 4 explains the adjustment in $P(t \geq T)$ and demonstrates how y gets adopted one period earlier.

Figure 4: Probability distribution of Markov time as P_q increases



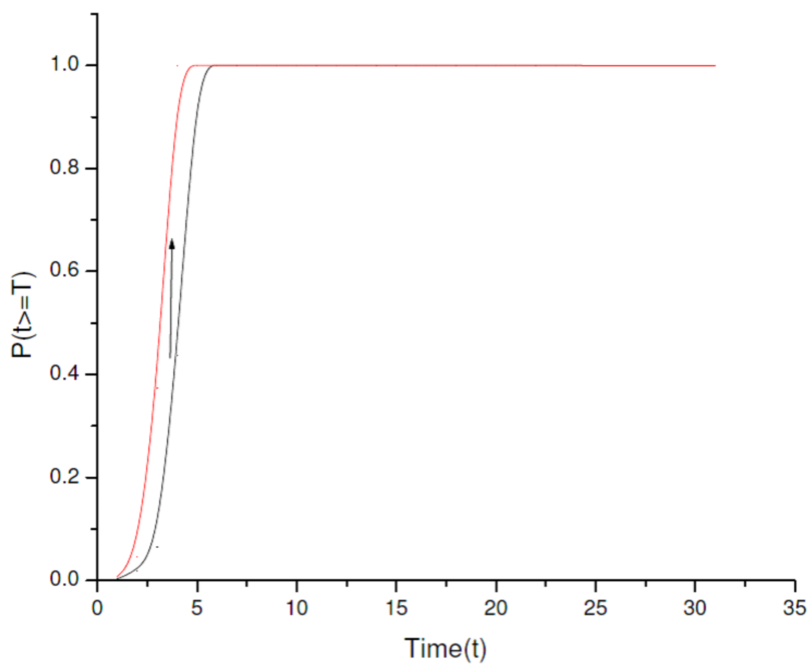
$q = 100, g' = 144, \lambda = 114, b = 0, \sigma = 10, \sigma_z = 10, A = 0.25, P_q(\uparrow) = 1\ to\ 1.1, P_g = 1.2$

Price Subsidy

Diverse regulations by the government reduce producers' cost of environment friendly changes in production technology or market price of consumption with salient environmental benefit. For example, lighting at business facilities accounts for 20 percent of all electricity sold in the United States. Still, the organizations seldom treat lighting as an opportunity for investment. The 'Green Lights' program promotes energy efficient lighting. Once a firm joins the Green Lights program, government provides assistance that reduces firms' cost of energy-efficient green lights. Similarly, the Direct and Counter-Cyclical Payment Program (DCP), administered by the U.S. Department of Agriculture's Farm Service Agency (USDA-FSA), made payments available for agricultural and forest sources of biomass production on private lands.[3] Additional subsidy programs are also available for conversion of biomass into energy.[4] Clearly, such subsidy policies keep the cost of G less than otherwise.

Let a subsidy program reduces P_g by 10% (from 1.2 to 1.08). Figure 5 explains this policy helps in adoption of y. As G becomes less expensive, $P(t \geq T)$ visibly increases and y is adopted one period earlier.

Figure 5: Probability distribution of Markov time as P_g decreases



$q = 100, g^{'} = 144, \lambda = 114, b = 0, \sigma = 10, \sigma_z = 10, A = .25, P_q = 1, P_g(\downarrow) = 1.2 \; to \; 1.08$

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[3] Please visit http://www.fsa.usda.gov/Internet/FSA_File/2011corsorsoylr.pdf for more information.

[4] Additional information is available at: http://www.window.state.tx.us/specialrpt/energy/subsidies/.

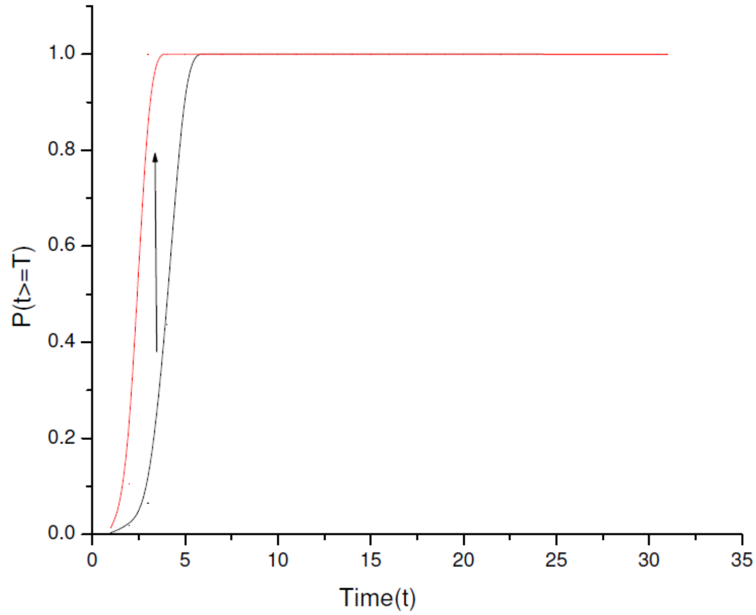
Information

Environmental pollution is often an unrecognized byproduct of our economic activities. However, we often fail to recognize and measure the impacts of these actions. As we strive for effective options for mitigating damaging impacts of pollution, information can play some critical roles. Reducing information asymmetry between consumers and producers can potentially facilitate environment friendly behaviors. Firms are often required to communicate environment-related information with their consumers, which at the same time can manifest the environmental track record of businesses. Eco-labels, for example, can make the product market more transparent (Crespi and Marrette 2005; Liere and Thidell 2005). Eco-labels have expanded from a mere dozen worldwide in the 1990s to more than 430 programs today.[5] Mandatory and voluntary corporate disclosure systems are increasing in applications and they replace or augment government regulations (Khanna 2001; Delmas and Montiel 2009).

However, reliability of information is crucial for making these programs effective. In essence, reliability of signals is reflected by their variance. The closer the signal is to the actual value, the stronger the consumer's expectation. It can be promptly spotted that if signals reflect only the true value adoption is immediate to availability. Instant adoption, though, is hardly possible. Let us suppose that variance of signals (σ_z^2) decreases from 100 to 25. The change in adoption behavior is shown in Figure 6. Probability of adoption clearly increases, as variance of the signals decreases.

[5] Please visit www.ecolabelindex.com for details.

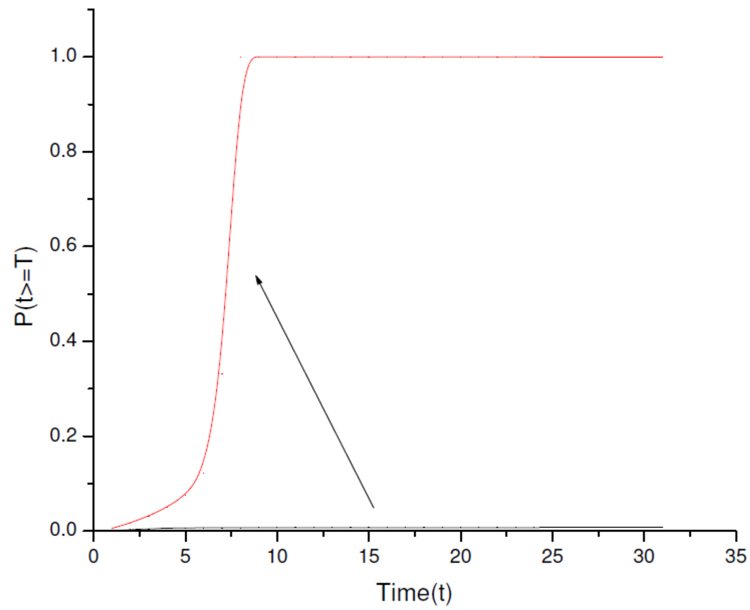
Figure 6: Probability distribution of Markov time as σ_z decreases



$q = 100, g' = 144, \lambda = 114, b = 0, \sigma = 10, \sigma_z(\downarrow) = 10 \; to \; 5, A = 0.25, P_q = 1, P_g = 1.2$

Diffusion of knowledge is another mechanism of information disclosure. Bollinger (2010) has explained adoption of green cleaning techniques by setting demonstration sites. Cantono and Silverberg (2009) have argued the reservation price (the maximum price a consumer agrees to pay) increases with number of existing consumers. Diffusion gives the consumers the opportunity to share others' experience and learn the purpose they are paying for. Equation (6) incorporates this concern and explains that the consumers are willing to spend more as they witness others spending on the same products. Realized improvement in environmental quality is subject to the fraction of the population in favor of *G*. If one percent of the population is convinced to adopt *G* with external means, adoption is possible in the situation described in figure (3). It is worth noticing that a small fraction of population helps an entire community to learn the benefit of *G* as shown in Figure 7, which results in adoption of technology *g*.

Figure 7: Diffusion of knowledge and probability distribution of Markov time



$q = 100, g' = 144, \lambda = 110, b = 0.1, \sigma = 10, \sigma_z = 10, A = 0.25, P_q = 1, P_g = 1.2$

6. Conclusion

The objective of this paper is to explain how sufficient market demand often results to adoption of eco-friendly technologies. Consumers' preference for salient environmental attributes in goods and services substitutes existing technologies with eco-friendly production processes. Adoption of green technologies is possible either by increase in consumers' concern for the environment, or by making it affordable for potential buyers. Although such technologies need to satisfy a threshold, adoption depends on a critical mass of society's concern for environmental protection. People may be interested even for minor environmental benefit if they are concerned enough.

If q and g are known qualities, consumer surplus from adoption of G can represent the magnitude of social welfare. The model can be extended to understand effectiveness of an adoption policy that results acceptance of G earlier enough to compensate the underlying cost of its implementation. Increase in research and development expenditure (R&D) and market size also helps adoption of green technologies. Increase in R&D improves quality of *G* and increase in potential market size decreases average burden on consumers. Since this study explains policy implications with existing market size for known quality of green technology, I have not raised these concerns. Still, they can be easily incorporated into the framework.

The model can be useful to evaluate a host of policy prescriptions for promoting adoption of green technologies. Further extension of this model may consider coexistence of green (x) and brown (y) in production. Also, while consumers learn the benefit from green products, producers also explore the potential market for their environmental preferences n. Therefore, future researchers may investigate a mechanism that can model and explain the simultaneous learning by the producers and consumers.

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APPENDIX

Computation of Posterior Means

For numerical estimation of $\overline{g_t}$, a vector of discrete values with reasonable difference (0.01) between each other is created in the beginning. It is assumed that $\overline{g_t}$ takes the discrete values in the assigned vector. The minimum value of $\overline{g_t}$ that meets the condition explained in equation (19) is the critical value of posterior belief to adoption of y. It is subject to a dynamic optimization problem as $V(q, F_{t+1})$ depends on the value of $V(q, F_t)$. The variance of posterior belief evolves in the process described in equation (11).

Distribution of Markov Time

In order to numerically estimate $P(t \geq T)$, I generate large number of streams of signals those are normally distributed with mean g and variance σ_z^2. The process creates a matrix of $S \times M$; M is number of streams generated and S is the final period to switch. For sufficiently large value of S, uncertainty tends to zero by the final period. The consumers get sufficient number of periods to decide if they want to adopt G or not. I set S=31 and the probability distribution of Markov time, $P(t \geq T)$, does not change as I increase the final period to decide (S) or the number of streams (M). Therefore, the results are consistent with increase in S and M. Since S represents t, from equation (9) starting from the first (t =1) for each row I compute,

$$\overline{z_t} = \frac{\overline{g_t}(t\sigma^2 + \sigma_z^2) - q\sigma_z^2}{t\sigma^2}$$

Let, for m_t out of M columns, $\overline{z_t} \geq \overline{z_t}^*$. Therefore, I conclude that $P(t = T) = \frac{m_t}{M}$. Since I consider no forgetting, as a consumer makes his/her mind, he/she does not change preference. Therefore,

$$P(t \geq T) = \begin{cases} \dfrac{m_t}{M} & if \quad t = 1 \\ P(t-1 \geq T) + \{1 - P(t-1 \geq T)\}P(t = T) & if \quad t > 1 \end{cases}$$

CHAPTER II:

POLLUTION TAX, HEALTH INSURANCE AND INFORMATION: A POLICY EXPERIMENT FOR PROMOTING ENERGY EFFICIENCY

1. INTRODUCTION

In this research I address the question whether residential energy conservation can be encouraged with public policy, and not private cost of electricity. I also address the inherent relation between energy conservation and health insurance as fossil fuel based power plants are major source of electricity, causing enough emission of green-house gases to increase health risk. During the study, 128 students of Florida International University were recruited to take part in 16 experimental sessions. Every session had 8 distinct participants. There were four parallel experimental setups, differentiated in combinations of option to buy health insurance and monitor others' choices. Every session was constituted of 3 sections of 30 decision-making rounds. While the participants pay a lump sum pollution-tax on every round of the 1st and 3rd section, it is proportional to the group expenditure on energy consumption during the 2nd section. The study reveals energy saving innate nature of people in response to health insurance and information, and compare relative benefit of proportional and lump sum pollution tax to group energy expenditure.

Environmental risks are often manmade, caused by pesticides, chemicals, radiation, air pollution, and water pollution. Such environmental degradations may cause anatomical or functional damages, irreversible physical changes and an increase in susceptibility to other biological, chemical or environmental stresses (Smith 1996; Wilby

2008; Luber 2008; Hill et al. 2009). Environmental protection programs, such as reduction in emission of greenhouse gases, are therefore a major area of researchers' attention (Haines et al. 2009). Combustion of fossil fuels is a major source of growing energy demand in the United States (U. S. Energy Information Administration 2012), causing emission of harmful greenhouse gases. According to the U.S. Energy Information Administration, 22% of total energy in the United States was generated by burning coal in 2011.[6] Particle pollution from existing coal power plants in the United States caused 13,200 premature deaths, 9,700 additional hospitalizations, and 20,000 heart attacks only in 2010 (Schneider and Banks 2010). The health-related damages, associated with air pollution from coal-fired power plants only, are estimated to cost more than $102 billion per year. Therefore, I discuss how to include altruistic values of energy conservation in a controlled lab-based behavioral experiment.

Human efforts to reduce emission, lead to environmental contribution and/or environment-responsible consumption choices. Buying carbon offsets is one of the simplest examples of environmental contribution, as the fund is utilized in projects like wind farms and replaces energy from fossil fuels.[7] Often consumers weigh quality of products over their environmental impacts, and pay more for what they perceive environmentally friendly (Ghazali and Simula 1997; Wasik 1996). Such consumption behavior is considered environment-responsible. Impure Public Goods (IPGs), in contrast, carry an environmental contribution and save money at the same time (Kotchen

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[6] Please visit http://www.eia.gov/energyexplained/ for further information.

[7] The airlines include a mandatory or optional contribution for carbon offsets in their flight tickets. Visit http://southafrica.to/transport/Airlines/Carbon-neutral-flight/Carbon-neutral-flight.php5 for details.

et al. 2003; Kotchen 2005). For example, fuel-efficient and/or hybrid vehicles cause less emissions with a smaller gasoline engine and save money on gas in comparison to their non-fuel efficient counterparts. Consumers of such vehicles therefore enjoy automobiles with lower gas consumption (private benefit) and reduced air emissions (environmental benefit). Most of the energy efficient residential installations fall in the same class of IPGS. Despite of their benefit, IPGs are still not popular choice of consumption. Environmental cost of consumption is often not reflected in retail prices of common merchandises. Therefore, non-environment friendly products are relatively inexpensive to IPGs (Morgan 2008). The price-gap is even higher since IPGs are relatively modern technologies. People are short sighted and underestimate future returns as a consequence of inconsistent high short-term discount rate (Camerer and Loewenstein 2004). The transaction costs of searching for and processing information (Jaccard et al. 2003; Wirl 2000), sensitivity to changes in attributes of energy services, and relative insignificance of energy costs as a proportion of total expenditure (Brown 2001; Levine et al. 1995; Jaffe and Stavins 1994; Sutherland 1991) also result in market failure of energy saving IPGs.

Researchers of psychological and contextual characterization, offer specific lessons for interventions that reduce residential energy use. For example, the utility-based decision literature discusses how to reduce residential energy use in two distinct approaches: economic engineering analysis and discrete choice modeling (Wilson and Dowlatabadi 2007). A rational individual's preference is guided by monetary cost-benefit analysis in the economic engineering analysis (Gayer and Viscusi 2012). Energy saving IPGs are relatively expensive and may face limited market success. The economic engineering analysis justifies market potential of such goods owing to their energy-efficiency gap (Mundaka et al. 2010). Their justification, however, turns out to limited success. Common interventions the economic engineering analysis suggests are, increase in per-unit cost of voltage (Gillingham et al. 2009) and price cut of energy efficient IPGs (Fuller et al. 2009). Still, their market acceptance is subject to limited success. A quest for an alternative explanation reveals several limitations of the economic engineering analysis. They are constant discount rate on future returns (Andrikopoulos 2012) and undiversified nonfinancial costs (Horne et al. 2005). Homogenous financial value does not recognize heterogeneity of decision-makers. Therefore, a stronger encouragement on social values for energy conservation becomes practically important (Stern 1999). It leads to the discrete choice models that capture choice dynamics. The discrete choice models guide the conscience of people (Dietz et al. 2009), to ensure market acceptance of energy-efficient appliances (Goulder and Parry 2009). We can refer to studies of value-belief-norm for example. Value-belief-norm of behavioral studies proposes a causal chain of human behavior with specific beliefs and responsibilities (Stern 2000). Social norms are personal obligations to act in a way that reduces adverse consequences (Groot and Steg 2009). It is related to self-expectations, and behavioral changes (Turaga et al. 2010).

In a laboratory based (at Florida International University, Miami, Florida) impure public good decision game, this paper presents the first systematic review of energy saving decision-making. Controlled laboratory based behavioral experiments can detail a decision scenario, while the key findings can be exploited to design real life policy interventions that improve energy saving behavior of the nation (Camerer 2004).

However, an appropriate context must be selected to match particular decision characteristics. Although the decision-making and behavioral literature is enriched in social science, the models widely vary in their basic assumptions, independent variables, structures and scales. The research tradition centers on an individual as the decision-maker, while sociologists question the relevance of individually framed decision models and emphasize the social and technological construction of behavior (Wilson and Dowlatabadi 2007). In an attempt, I introduce a pollution liability tax policy that aims the public benefit of energy conservation. While an expert opinion suggests consumption of energy saving appliances, the rule of thumb such as do not waste leads to a deviation from the expert model (Thaler 1980; Mogilner and Aaker 2009). Therefore, I discuss how emphasize on common benefit changes people's behavior and increases energy saving. In an attempt to integrate financial limitation to market acceptance of energy-saving residential installations because of non-monetary cost of adoption, I have considered energy-saving residential investments are non-beneficial in absence of social benefit in the decision-making experiment. I have also addressed the implicit relation between health insurance on energy conservation, which has never come to the researchers' notice.

I have explained this study in following sections. The second section describes the experimental design. The non-parametric estimation result is discussed in the third section. The third and fourth sections describe participants' characteristics and discuss the estimation results, respectively. I have discussed the findings in the sixth section.

2. ENERGY SAVING EXPERIMENT

During the study, 128 subjects were recruited at the south campus of Florida International University (Miami, Florida). Subjects were undergraduate or graduate students, and participated in one of 16 decision-making sessions in groups (8 subjects per group). University students were informed that a session would last for 2 hours and they could earn $10 to $50 on the basis of decisions they made. Subjects were recruited on first come first serve basis and assigned to designated-computers upon arrival. Instructions were read and explained every session.[8] Subjects were not allowed to communicate among themselves during the experiment. I designed four parallel experimental setups, to find possible impact of health insurance and information on energy saving choices. The decision-making experiments are described in the following subsections.

Experiment One

Experiment one is divided in 3 sections, 30 rounds each. Every round represents a year, and each section stands for a stretch of 30 years (Table 1). The experimental set-up is described in Figure 8. In the beginning of every section, subjects are given a savings account balance of $60,000. In addition, they earn a $50,000/round salary and a 3% annual interest on their savings account balance. Subjects also have expenses, $30,000/round on everyday necessities, $2,000/round of electricity-bill, and $300/round of environmental tax (Green Tax). Subjects may choose to reduce their energy bill with long-term clean energy-generating installations (ESC^{LT}) and short-term energy saving choices (ESC^{ST}). Once installed, ESC^{LT} are effective for the remaining section (all

[8] Experimental detailed instructions are available on request.

remaining rounds). There are three ESC^{LT}: Geothermal Heat Pump (GHP), Residential Wind Turbine (RWT), and Residential Solar Energy System (RSES). Installation costs of GHP, RWT and RSES are $7000, $8000, and $15000, and they save $200, $200, and $400 of energy bill every round, respectively. There are two ESC^{ST}, Energy Efficient Lighting (EEL) and Energy-Conservation Behavior and Energy Efficient Appliances (ECB), effective for one round only. The costs of EEL and ECB are $100 and $200, and they save $60 and $140 of energy bill.[9]

Subjects are at a health-risk, 60% probable every round. As a subject gets exposed to the risk, half the times it is too trivial to cause any medical expenditure (see Figure 10). In 47% of the cases when a subject gets exposed to the risk, medical expenses are in the range of $1,000 and $5,000 (Minor sickness event; see Figure 11). Remaining 3% of the exposures to health-risk cause major medical expenses between $10,000 and $60,000 (Major sickness event; see Figure 12).

Energy production in the United States heavily depends on combustion of fossil fuels, which causes emission of greenhouse-gases and consequently increases the emission-related health-risk. Therefore, energy conservation reduces health-risk and every $200 reduction in group-energy-bill (total energy bill by eight subjects in one round) is set to reduce probability of the health-risk by 1% in the experiment. The major and minor sickness events consequently become less frequent (see Appendix).

Thirty-two subjects participated in four sessions of Experiment One. While the first (Baseline) and the third (Repeated Baseline) sections are as explained as above, I

[9] We have explained a particular decision made by a subject with ESC^{LT} and ESC^{ST} in Figure 9.

apply either of the following two treatments in the second section (Treatment).

A) Increasing Green Tax (IGT): The Green Tax increases to \$500/round from \$300/round following the 10^{th} round, if the group energy bill does not drop by 30% (from \$16,000 to \$11,200).

B) Decreasing Green Tax (DGT): Green Tax is \$500/round for the first nine rounds. If the group energy bill drops by 30% by 10^{th} round, Green Tax reduces to \$300/round from \$500/round. Green Tax is \$500/round even after 10^{th} round, if the group energy bill does not drop by 30%.

I coordinated four sessions, two for each of the IGT and the DGT treatment. Subjects receive \$1 (US dollar) for every \$30,000 (Lab dollar) of their savings account balance after 30 rounds in one of the three sections, selected randomly.

Experiment Two

Subjects may purchase one of two health insurance (HI) policies during Experiment Two. The first insurance policy (Ins1) has a \$1,000 premium, and 35% co-pay with \$20,000 cap. The second insurance policy (Ins2) has a \$1,300 premium, and 10% co-pay with \$5,000 cap. Both the insurance policies are effective for a round only. The energy saving choices and circumstances (see Figure 13), as well as number of sessions per treatment, remains the same as Experiment One.

Experiment Three

During Experiment Three, subjects monitor others' decisions (MOD) or observe the aggregate energy saving choices made by others (see Figure 14). The energy saving context, and number of sessions per treatment, remains the same as Experiment One.

Experiment Four

This is a combination of Experiment Two and Experiment Three. That is, subjects may purchase a health insurance policy and monitor the aggregate energy saving choices by others. I coordinated 4 sessions, 2 for each of IGT and the DGT treatment.

3. NONPARAMETRIC ESTIMATION

Table 2 reports the average energy conservation across sections and experiments. In 2 out of 4 experiments, average energy conservation is higher during IGT than the Baseline. Similarly, average energy conservation is higher during IGT than the Repeated Baseline in 3 out of 4 experiments. Decreasing Green Tax (DGT) treatment seems to be more efficient than IGT, as average energy saving is higher during DGT in 3 out of 4 experiments with the Baseline and 4 out of 4 experiments with the Repeated Baseline.

I have compared energy saving choices (ESC) across sections using six dummy variables. To get a better sense of them, Table 3 reports the dummy variables with their mean and standard deviation. Three of those dummies (*GEOTHERMAL*, *WIND*, and *SOLAR*) stand for the round (1 to 30) in which an ESC^{LT} (GHP, RWT and RSES) is made, and set to 31 otherwise. Since ESC^{LT} are effective for a section, lower entries (close to 1) of these dummies represent maximum energy saving. On average, subjects chose GHP, RWT, and RSES roughly on the 7th round, 10th round, and 7th round. *LIGHT* and *APPLIANCE* are two other dummy variables, which represent how many rounds (0 to 30) a subject chooses EEL and ECB in 30 rounds of one section. Hence, less energy is saved as *LIGHT* and *APPLIANCE* take minor values (inclined to 0). On average, subjects choose EEL and ECB approximately for 16 and 18 rounds every section. The last dummy variable I generated, *EXPENDITURE*, is a subject’s undiscounted total expenditure on

ESC. There is one value of each dummy and for every section. Therefore each dummy has 384 observations (128 subjects x 3 sections) in total.

I have reported significant difference in ESC in response to IGT, DGT, HI, and MOD using the Wilcoxon signed-rank and rank-sum test and t-Test in Table 4. Since the same set of subjects made decisions for three sections (Baseline, Treatment, and Repeated Baseline), I used the Wilcoxon signed-rank test to find comparative energy saving benefit of IGT and DGT (Treatment) over Baseline and Repeated Baseline. In contrast, I find impact of HI and MOD with Wilcoxon ranked-sum test as different sets of subjects participated across four experiments (Muenchen and Hilbe 2010). The Wilcoxon signed-rank test shows rare implication of earlier or frequent energy saving long-term or short-term choices in response to IGT. Although I find significant evidence that RWT and RSES are chosen earlier ($p < 0.07$) during IGT treatment compared to the Baseline, the result is lost as I do a t-Test. However, earlier choice of RSES is significant by both Wilcoxon signed-rank and t-Test, compared to the Repeated Baseline ($p < 0.07$). Effectiveness of DGT treatment is equivalent. Although there is indication of choosing RSES earlier during DGT than the Baseline ($p < 0.00$), it is inconsistent with t-Test result. Earlier choice of RSES is significant by both the Wilcoxon signed-rank and t-Test, as compared to the Repeated Baseline ($p < 0.02$). The Wilcoxon signed-rank test also indicates frequent choice of ESC^{ST} as DGT is in effect, compared to the Repeated Baseline ($p < 0.01$). Except for the RSES, there is strong evidence that ESC^{LT} are delayed and ESC^{ST} are chosen less frequently as subjects have choice to purchase health insurance ($p < 0.08$) both by the Wilcoxon rank-sum and t-Test. The undiscounted total expenditure on ESC also significantly decreases ($p < 0.00$) in response to HI. There is no or incompatible evidence of MOD's effectiveness by Wilcoxon rank-sum and t-Test.

A visual representation of average energy conservation across 30 rounds, for different sections and decision-making set-ups, is given in Figure 15. It can be seen that average energy conservation is higher across 30 rounds during the 2nd section (IGT or DGT), compared to the 1st and 3rd section (Baseline and Repeated Baseline). Average energy saving during the DGT section, however, gets close and even below the average energy saving during the baseline following the 22nd round. Also, average energy conservation is lower every round as subjects have the option to buy HI, irrespective of whether they monitor others decisions and not. Average energy conservation is clearly a lesser amount as subjects monitor others' decisions (MOD) all 30 rounds, in absence of option to buy HI. In presence of option to buy HI, average energy conservation increases faster while subjects monitor others' decision, and exceeds average energy conservation while subjects do not monitor others' decision by 18th round.

4. CHARACTERISTIC VARIABLES

Energy efficiency reduces emission of greenhouse-gases and consequently lowers the emission-related health-risk. Therefore, individual risk preference may be critical in energy saving choices made by subjects. I elicited subjects' risk-aversion using the Holt and Laury's mechanism (Holt and Laury 2002). Energy saving choices of subjects may change based on their social and demographic characteristics also. Hence the subjects replied to a survey of 12 questions, which elaborates their human ecology and document their diverse perspectives about the importance of energy conservation.

The subject specific characteristic variables are clarified in Table 5. Of the 128 subjects, 61 were female and 67 were male. Their average age was 26, in the middle of 18 rounds and 39 rounds. Among the subjects 24 are White, 10 are African-American, 41 are Hispanic, 52 are Asian, and one is American Indian. I also took account of their round of study as 3 of them were freshman, 6 were sophomore, 18 were junior, 26 were senior, and 75 were graduate student. Beside their round at school, they also informed their major. Academic major of 23 subjects was Economics, 12 subjects had major in Social Science other than Economics, 22 subjects were in Math, Statistics, Computer Science or Engineering, 39 subjects were in Natural Science, 4 subjects were in Business, 9 subjects were in Arts, and 29 subjects had major in other academic disciplines. The subjects also chose their party affiliation: Democrat, Republican, and Independent. While 46 of the subjects identified their political affiliation as Democrats, 71 were Republic and 11 were Independent. Special emphasis was placed on documenting diverse concern for the environment and the society, and on belief that conservation of energy saves the environment. On a scale of 5 points (0 to 4), subjects were asked to rank their concern for the society and for the environment, where 0 represents 'very concerned' and 4 stands for 'not at all concerned'. Similarly, subjects articulated themselves in belief that 'conservation of energy saves the environment' and 'environmental pollution causes health issues' on a scale of 0 to 4. The scale reads, '0 = Really believe so' and '4 = Do not believe so, at all'. On average, subjects seem to be very concerned for the society and the environment. They also seem to believe that conservation of energy saves the environment and environmental pollution causes health issues.

5. PANEL DATA ESTIMATION

The between subject and group design of the experiment implies treatments and groups will be highly correlated. In regression analysis, simply including a group identity variable for different sessions would obscure treatment effects. In addition, although I have measured any systematic way of behaving by individual characteristics, some unobservable effects may be missing. Therefore, I have applied generalized panel random effect estimation (Wooldridge 2002; Davidson and MacKinnon 2004) and set subject-id as the cross-sectional or group variable. Subjects make choices 30 rounds for 3 consecutive sections, 90 rounds in total. Therefore, the time variable for panel estimation is set 1 to 90. The dependent variable of the regression analysis if energy conservation, or the difference between regular energy bill ($2,000) and energy bill a subject pays after making energy saving choices. The estimations are undertaken using *xtgls* estimation in STATA release in 11. I have explained the dependent and independent variables in Table 5 and 6, and have presented the estimation result of six different specifications in Table 7.

I have found robust and consistent estimation inference that IGT and/or DGT increases energy conservation at 1% level of significance. Conservation of energy decreases as subjects get choice to purchase HI, at 5% or 10% significance level. The estimation result suggests subjects, who buy either Ins1 or Ins2, spend more on ESC. Similar to the non-parametric estimation results, there is no significant increase in energy conservation as MOD is in effect. Impact of initial energy conservation (energy conservation on period 1) of subjects is robust and increases energy conservation for the rest of the section at 1% significance level. Initial energy conservation of subjects represents the importance of energy saving innate nature of people (Kirman and Teschl

2010; Poortinga et al. 2004). Energy conservation seems to decrease as a subject progresses through the sections (Baseline to Treatment to Repeated baseline) at 1% level of significance. Hence, I conclude subjects decrease their expenditure on ESC through sections, as they learn the nature of the experiment. Energy conservation also increases as subjects move along a section, making repeated energy saving decisions over 30 rounds, at 1% significance level. The estimation result suggests that energy conservation increases with environmental concern and decreases with concern for the society, at 1% to 3% level of significance. Most of the subject's characteristics are not significant determinant of energy conservation. However, I found few incidents where energy conservation is less for female subjects than male subjects. Although not consistent in all six regression-specification, American Indian subjects save less energy and African American subjects save more energy at 1% to 3% level of significance in comparison to Hispanic subjects of the experiment.

6. CONCLUSION

The experimental design of this study incorporates major limitations to market success of energy saving residential installations into consideration. Subjects' energy bill is set fifteenth part of their consumption expenditure and twenty-fifth part of their annual income, since one of the major limitations to market success of energy saving residential installations is the relative insignificance of energy costs to total expenditure. As energy efficiency gap is negligible, consumers may find energy saving residential installations not profit maximizing in presence of transaction costs of searching for and processing information. I have incorporated this concern, as ESC^{LT} and ESC^{ST} are not beneficial in absence of health benefit.

The parametric and non-parametric estimation results a considerable number of findings. Firstly, there is no significant estimated energy saving benefit from MOD. Subjects may increase or decrease their energy saving expenditure in response to information. Environmental contribution of subjects may be substitute and negatively related (Andreoni 2006; Powell and Steinberg 2006; Kolm and Ythier 2006), or complementary and proportionate (Bardsley 2000; Croson 2007; Fischbacher et al. 2001) to contribution of others. Therefore, information may be advantageous, disadvantageous, or of no significance to energy saving, on the basis of its relative strength. Secondly, energy conservation decreases with option to buy health insurance. However, subjects reduce their energy consumption as they purchase either of Ins1 and Ins2. The result seems self-contradictory; but can be explained. The search leads us to implications of 'Moral Hazard' and 'Moral Imperative'. In the experimental design, HI policy and reduction in energy bill are perfect substitute, since both reduce expected medical expenditure (Laffont 1995). Therefore, energy saving effort of an average participant reduces with exposure to HI. On the contrary, as a subject purchase health insurance, a reverse principle originates inside his mind to act on environmental protection. The reverse principle is known as moral imperative (Postma and Smeyers 2012). Therefore two opposite forces, moral hazard and moral imperative, determine the ultimate influence of HI on energy saving. Moral imperative decreases with opportunity cost (Turaga et al. 2010), and is weaker for Ins2 to Ins1. Thirdly, although I do not find enough evidence by the non-parametric estimation results, the parametric estimation result confirms both IGT and DGT policy interventions significantly increase energy saving. The estimation result suggests DGT policy intervention saves more energy than IGT, since expected financial gain is better incentive than anticipated monetary loss (Levitt et al. 2012).

There is specific reason why I advocate policy regulation on public benefit of energy conservation (i.e., Green Tax) and not private cost of electricity (i.e., voltage cost), promoting energy saving. James Androi (1990) has explained why people give to charity by proposing people receive utility from the act of giving, known as warm-glow giving. Energy-saving residential installations and behavioral practices save money on electricity consumption (private benefit) and decrease air-emission/air-pollution (public benefit). Therefore, ESCs contribute in environmental protection and also save money on energy. As per unit of voltage increases, ESCs become more profitable. However, their environmental contribution does not change. Contributions are higher when more people are benefitted in return, holding per-person benefit the constant (Goeree 2002). Public measure to support green electricity is indispensable (Memges et al. 2005) and although voluntary environmental contracts should not be expected to function as the exclusive tool of environmental policy, they provide a niche market for both existing electric utilities and new energy supply companies (Kotchen et al. 2001). As motivations for environmental contributions are poorly determined by rational self-interested behavior, energy saving should also be encouraged with policies that target public benefit.

Public insurers such as Medicare and Medi-Cal have a lot to gain from cleaner air, so as employers and private insurers. Pollution-related health care costs drive up employees' health insurance premiums and increases costs for the many employers who contribute to those premiums (Cutler 2002; Lawson and Nemec 2003). Workers may also pay directly for pollution, as higher insurance premiums translate into lower wages

(Chernew et al 1997; Olson 2002; Baicker and Chandra 2006). Insurers make lower profits if health insurance premiums do not increase as much as medical spending does due to dirty air, and vice versa. In short, everyone benefits from cleaner air (Romley et al. 2010). Energy efficiency seems to be crowded out when subjects have the option to buy health insurance to cover pollution related health risks. Therefore an interdisciplinary policy is strongly recommended that translate energy saving into reduction in air pollution, and generates benefit in premiums and deductibles of health insurance policies.

The study has certain limitations. Although there is enough evidence that most energy saving choices increase private benefit in the long run, I considered them non-beneficial in absence of decrease in medical risk in the experimental set-up. It is not beyond argument, but justified since behavioral researches should explore interventions with the maximum potential environmental-impact rather than the greatest theoretical or experimental interest (Stern 2000). However, default knowledge of benefit from energy saving choices may partially influence decisions. Also, a particular section of the population (students) took part in the experimental sessions. Students may not be responsible family members to pay for electricity, medical bills, and other household expenditures. Therefore, confirming the results with household surveys will guide better policy designs.

In future, this study might be elaborated to solve several other aspects of human behavior in energy use. We can study change in energy saving choices, as subjects monitor others' decisions after a considerable number of rounds and not always. Any significant change in their choice would enrich scholarly studies on information limit.

Also, as we increase per unit cost of electricity instead of influencing the Green Tax, we can compare relative efficiency of private and public incentive on energy saving.

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APPENDIX

Medical Emergency, Allied Expenses, and Benefit from Reduction in Energy Bill

Probability of Medical Emergency = P (Medical Emergency) = 0.60

Probability of Negligible Medical Emergency
= P (Negligible Medical Emergency/Medical Emergency)
= P (Negligible Medical Emergency) x P (Medical Emergency) = 0.50x0.60 = 0.3

Probability of Minor Medical Emergency
= P (Minor Medical Emergency/Medical Emergency)
= P (Minor Medical Emergency) x P (Medical Emergency) = 0.47x0.60 = 0.282

Probability of Major Medical Emergency
= P (Major Medical Emergency/Medical Emergency)
= P (Major Medical Emergency) x P (Medical Emergency) = 0.03x0.60 = 0.018

Mean medical expense of 'Negligible Medical Emergency' = $0

Mean medical expense of 'Minor Medical Emergency' = $3,000

Mean medical expense of 'Major Medical Emergency' = $35,000

Expected medical expense of every participant/round
= $(0 x 0.3 + 3,000 x 0.282 + 35,000 x 0.018)/round
= $1,476 /round

Decrease in $200 of total energy bill reduces Probability of Medical Emergency by 1%. Therefore, expected medical expense of every participant per round decreases by, ($1,476/60) = $24.6.

Private and Social Benefits of ESC^{ST} and ESC^{LT}

Private and social benefits of ESC^{ST}:

Private benefit of EEL (per round) = Reduction in energy bill = \$60

Social benefit of EEL (per round) = Reduction in energy bill + Reduction in group's total expected medical expenses = \$60 + (60/200) x \$24.6 x 8 = \$119.04

Private benefit of ECB (per round) = Reduction in energy bill = \$140

Social benefit of ECB (per round) = Reduction in energy bill + Reduction in group's total expected medical expenses = \$140 + (140/200) x \$24.2 x 8 = \$277.76

Present value calculations of private and social benefits of ESC^{LT}:
(If Round = 1)

Discount Rate = d = 1/(1+Rate of Interest) = 1/1.03

A = $(1-d^{30})/(1-d)$ = 20.19

Discounted present value of private benefits of GHP = Discounted present value of reduction in energy bill = A x \$200.00 = 20.19 x \$200.00 = \$4,038.00 (approximated to two decimals)

Discounted present value of social benefit of GHP (per round) = Reduction in energy bill + Reduction in group's total expected medical expenses = A{\$200 + (\$200/\$200) x \$24.6 x 8} = 20.19 x \$396.80 = \$8,011.39 (approximated to two decimals)

Discounted present value of private benefits of RWT = Discounted present value of reduction in energy = A x \$200.00 = 20.19 x \$200.00 = \$4,038.00 (approximated to two decimals)

Discounted present value of social benefit of RWT (per round) = Reduction in energy bill + Reduction in group's total expected medical expenses = A{\$200 + (\$200/\$200) x \$24.6 x 8} = 20.19 x \$396.8 = \$8,011.39 (approximated to two decimals)

Discounted present value of private benefits of RSES = Discounted present value of reduction in energy bill = A x \$400 = 20.19 x \$400.00 = \$8,076.00 (approximated to two decimals)

Discounted present value of social benefit of RSES (per round) = Reduction in energy bill + Reduction in group's total expected medical expenses = A{\$400 + (\$400/\$200) x \$24.6 x 8} = 20.19 x \$793.6 = \$16,022.78 (approximated to two decimals)

TABLES

Table 1: Experimental design

Part One	Part Two			Part Three
The Holt and Laury risk-aversion test	Experiment with energy saving options			Socio-demographic survey
	Baseline	Treatment (IGT or DGT)	Repeated Baseline	
10 Choices	30 Rounds	30 Rounds	30 Rounds	12 Responses

Table 2: Average energy saving by treatment

Sessions		Baseline	Treatment	Repeated Baseline
Experiment One: ESC	IGT	762.38 (296.06)	807.08 (309.02)	853.33 (270.44)
	DGT	808.96 (277.49)	845.50 (234.50)	773.79 (317.29)
Experiment Two: ESC + HI	IGT	670.79 (334.96)	654.08 (324.63)	572.50 (387.96)
	DGT	812.83 (201.10)	755.08 (254.99)	680.58 (306.62)
Experiment Three: ESC + MOD	IGT	663.95 (277.44)	659.17 (281.05)	645.06 (317.52)
	DGT	815.29 (301.88)	857.54 (231.69)	782.42 (343.17)
Experiment Four: ESC + HI + MOD	IGT	712.92 (364.01)	847.29 (204.05)	680.88 (381.27)
	DGT	630.71 (244.38)	681.54 (235.08)	534.96 (305.31)

Note: ESC represents 'Energy saving Choices', **ESC^{LT}** represents 'Long Term Energy Saving Choices', **ESCST** represents 'Short Term Energy Saving Choices', **HI** represents **'**Health Insurance', and **MOD** represents **'**Monitor Others' Decision'

Table 3: Summary statistics of decision variables for non-parametric estimation

Variable	**Definition**	**N**	**Baseline**	**Treatment**	**Repeated Baseline**
GEOTHERMAL	Period on which respondent chooses to invest in GHP (1 to 30), 31 otherwise	384	5.81 (9.47)	6.40 (10.16)	8.11 (11.40)
WIND	Period on which respondent chooses to invest in RWT (1 to 30), 31 otherwise	384	9.20 (11.62)	8.45 (11.35)	9.90 (11.16)
SOLAR	Period on which respondent chooses to invest in RSES (1 to 30), 31 otherwise	384	7.05 (10.46)	4.97 (8.43)	8.71 (11.86)
LIGHT	Number of time the participant chooses EEL in 30 rounds (0 to 30)	384	17.14 (10.46)	17.04 (11.56)	16.45 (12.40)
APPLIANCE	Number of time the participant chooses ECB in 30 rounds (0 to 30)	384	18.97 (10.71)	18.75 (11.44)	18.13 (12.30)
EXPENDITURE	Undiscounted total expenditure ($) on GHP, RWT, RSES, EEL, and ECB	384	30,828.13 (10,517.48)	31,852.34 (8,891.21)	29,216.41 (12,334.88)

Note: Three observations (one for every section) for each of 128 participants

Table 4: Non-parametric test results

Dummy Variable		*GEOTHERMAL*		*WIND*		*SOLAR*		*LIGHT*		*APPLIANCE*		*EXPENDITURE*	
		RANK	t-Test	RANK	t-Test	RANK	t-Test	RANK	t-Test	RANK	t-Test	RANK	t-Test
IGT	BSL	0.03 (0.98)	-1.03 (0.55)	3.28*** (0.00)	2.06 (0.33)	1.79* (0.07)	2.53 (0.17)	-0.09 (0.93)	-0.05 (0.98)	0.42 (0.67)	0.73 (0.71)	-1.22 (0.22)	-1779.69 (0.35)
	RPBSL	0.45 (0.65)	0.48 (0.79)	1.47 (0.14)	1.52 (0.47)	2.35** (0.02)	3.48* (0.07)	-0.85 (0.40)	0.06 (0.98)	-0.75 (0.46)	0.33 (0.87)	-2.42** (0.02)	-2631.25 (0.20)
DGT	BSL	-0.34 (0.73)	-0.14 (0.94)	0.00 (1.00)	-0.55 (0.78)	2.86*** (0.00)	1.63 (0.29)	0.18 (0.86)	0.25 (0.90)	-0.80 (0.42)	-0.30 (0.88)	-0.93 (0.35)	-268.75 (0.86)
	RPBSL	1.48 (0.14)	2.93 (0.14)	0.72 (0.47)	1.39 (0.51)	3.05*** (0.00)	4.00** (0.02)	-1.57 (0.12)	-1.25 (0.56)	-2.62*** (0.01)	-1.56 (0.47)	-2.53** (0.01)	-2640.63 (0.14)
HI	WIMDO	-2.02** (0.04)	-4.51*** (0.00)	-1.86* (0.06)	-5.52*** (0.00)	-0.11 (0.91)	-2.05 (0.15)	3.91*** (0.00)	6.64*** (0.00)	2.98*** (0.00)	5.46*** (0.00)	4.22*** (0.00)	5140.63*** (0.00)
	WOMDO	-1.73* (0.08)	-3.77* (0.01)	0.26 (0.79)	-2.10 (0.21)	0.25 (0.81)	-2.33 (0.15)	5.15*** (0.00)	8.09*** (0.00)	4.16*** (0.00)	6.66*** (0.00)	4.86*** (0.00)	5078.13*** (0.00)
MDO	WIHI	-0.49 (0.62)	-0.65 (0.71)	-1.71* (0.09)	-2.95 (0.11)	-0.63 (0.53)	0.84 (0.61)	0.42 (0.68)	0.22 (0.89)	1.57 (0.12)	0.44 (0.77)	-0.12 (0.90)	-244.79 (0.88)
	WOHI	-0.25 (0.80)	0.09 (0.94)	-0.15 (0.88)	0.47 (0.75)	-0.63 (0.53)	0.56 (0.67)	1.90* (0.06)	1.68 (0.27)	-0.30 (0.77)	-0.76 (0.65)	1.66* (0.10)	-307.29 (0.82)

Note: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are p-values
The RANK-test represent the signed-rank or rank-sum test, as applicable. The null hypothesizes are as follows:

H_0 (BSL)**:** **Dummy Variable** (Baseline) = **Dummy Variable** (IGT/DGT)
H_0 (RPBSL)**:** **Dummy Variable** (Repeated Baseline) = **Dummy Variable** (IGT/DGT)
H_0 (WIMDO)**:** **Dummy Variable** (Without HI, with MDO) = **Dummy Variable** (With HI, with MDO)
H_0 (WOMDO)**:** **Dummy Variable** (Without HI, without MDO) = **Dummy Variable** (With HI, without MDO)
H_0 (WIHI)**:** **Dummy Variable** (With HI, without MDO) = **Dummy Variable** (With HI, with MDO)
H_0 (WOHI)**:** **Dummy Variable** (Without HI, without MDO) = **Dummy Variable** (Without HI, with MDO)

Table 5: Summary statistics of risk-aversion and socio-demographic responses

Variable	**Description**	**N**	**M**	**SD**
AVERSION	Holt and Laury risk-aversion index (1 to 9)	128	6.70	2.13
AGE	Age of the respondent	128	25.82	4.34
FEMALE	1 if Female; 0 otherwise	128	0.48	0.50
WHITE	1 if White; 0 otherwise	128	0.19	0.39
BLACK	1 if African-American; 0 otherwise	128	0.08	0.27
ASIAN	1 if Asian, 0 otherwise	128	0.41	0.49
AMEIND	1 if American Indian or Alaska Native; 0 otherwise	128	0.01	0.09
LIBERAL	Political orientation of respondent (0 = Extremely liberal, 1 = Liberal, 2 = Slightly Liberal, 3 = Middle of the road, 4 = Slightly conservative, 5 = Conservative, 6=Very conservative)	128	2.41	1.49
REPUBLIC	1 if Republican; 0 otherwise	128	0.09	0.28
INDEPENDENT	1 if Independent; 0 otherwise	128	0.55	0.50
ECONOMICS	1 if majoring in Economics; 0 otherwise	128	0.10	0.30
SOCIAL	1 if majoring in Social Science (other than Economics); 0 otherwise	128	0.09	0.29
MATH	1 if majoring in Math, Statistics, Computer Science or Engineering; 0 otherwise	128	0.17	0.38
NATURAL	1 if majoring in Natural Science; 0 otherwise	128	0.30	0.46
BUSINESS	1 if majoring in Business; 0 otherwise	128	0.03	0.17

ARTS	1 if majoring in Arts, Language etc; 0 otherwise	128	0.07	0.26
OTHER	1 if majoring in other subjects; 0 otherwise	128	0.23	0.42
SCHOOL	School round (0 = Freshman, 1 = Sophomore, 2 = Junior, 3 = Senior, 4 = Graduate Student)	128	3.28	1.03
HEALTH	How strongly the respondent believes that environmental pollution causes health issues (0 to 4; 0 = Really believe so, 4 = Do not believe so, at all)	128	0.22	0.50
ENERGY	How strongly the respondent believes that conservation of energy saves the environment? (0 to 4; 0 = Really believe so, 4 = Do not believe so, at all)	128	0.43	0.77
ENVIRONMENT	Environmental concern of respondent: (0 to 4; 0 = Really believe so, 4 = Do not believe so, at all)	128	0.57	0.76
SOCIETY	Concern for other people/society: (0 to 4; 0= Very concerned, 4 = Not at all concerned)	128	0.55	0.86

Notes: Male (*MALE*), Hispanic (*HISPANIC*), Democrat (*DEMOCRAT*), and major in arts, language (*ARTS*) are dropped to avoid multicollinearity problem, and we drop Native Hawaiian or Other Pacific Islander (*PACISLAN*) due to no observation.

Table 6: Summary statistics of experimental data

Variable	Definition	N	M	SD
CONSERVATION	Energy saving ($2,000 – Household energy bill)	11,520	729.53	309.35
INICONSER	Conservation of energy (*ROUND* = 1)	11,520	429.01	292.84
SECTION	Section index (1 to 3)	11,520	2	0.82
ROUND	Round index (1 to 30)	11,520	15.50	8.66
TIME (t)	t^{th} decision of participant (1 to 90, 30 rounds per section)	11,520	45.50	25.98
INFORMATION	1 if participant receives the information of others' choices; 0 otherwise	11,520	0.50	0.50
INSOPT	1 if HI is available; 0 otherwise	11,520	0.50	0.50
INSONE	1 if Ins1 is chosen; 0 if Ins1 is not chosen	11,520	0.12	0.33
INSTWO	1 if Ins2 is chosen; 0 if Ins2 is not chosen	11,520	0.26	0.44
INCREASE	1 for treatments of IGT, 0 otherwise	11,520	0.17	0.37
DECREASE	1 for treatments of DGT, 0 otherwise	11,520	0.17	0.37

Note: 90 observations for each of 128 participants (11,520 = 90 x 128)

Table 7: Regression result (Dependent variable, *CONSERVATION*)

	(1)	(2)	(3)	(4)	(5)	(6)
	CONSERVATION	*CONSERVATION*	*CONSERVATION*	*CONSERVATION*	*CONSERVATION*	*CONSERVATION*
INICONSER	0.363^{***}	0.364^{***}	0.363^{***}	0.365^{***}	0.364^{***}	0.363^{***}
	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)
INCREASE	0.022^{***}	0.022^{***}	0.022^{***}	0.022^{***}	0.022^{***}	0.022^{***}
	(4.526)	(4.527)	(4.526)	(4.526)	(4.526)	(4.526)
DECREASE	0.054^{***}	0.054^{***}	0.054^{***}	0.054^{***}	0.054^{***}	0.054^{***}
	(4.476)	(4.477)	(4.476)	(4.476)	(4.476)	(4.476)
INSOPT	-0.177^{***}	-0.172^{***}	-0.175^{***}	-0.173^{***}	-0.169^{***}	-0.155^{***}
	(39.10)	(38.67)	(38.58)	(35.10)	(37.23)	(37.00)
INSONE	0.038^{***}	0.038^{***}	0.038^{***}	0.038^{***}	0.038^{***}	0.038^{***}
	(7.615)	(7.617)	(7.615)	(7.614)	(7.615)	(7.614)
INSTWO	0.025^{**}	0.025^{**}	0.025^{**}	0.025^{**}	0.025^{**}	0.025^{**}
	(7.809)	(7.810)	(7.809)	(7.805)	(7.808)	(7.808)
INFORMATION	-0.053	-0.044	-0.053	-0.024	-0.042	-0.038
	(36.81)	(36.20)	(36.44)	(34.60)	(35.51)	(35.24)
ROUND	0.165^{***}	0.165^{***}	0.165^{***}	0.165^{***}	0.165^{***}	0.165^{***}
	(0.172)	(0.172)	(0.172)	(0.172)	(0.172)	(0.172)
SECTION	-0.055^{***}	-0.055^{***}	-0.055^{***}	-0.055^{***}	-0.055^{***}	-0.055^{***}
	(1.834)	(1.834)	(1.834)	(1.834)	(1.834)	(1.834)

AVERSION	0.006	-0.001		0.019		
	(8.785)	(8.605)		(7.999)		
AGE	0.036	0.012			0.026	0.032
	(3.486)	(3.535)			(2.993)	(2.994)
FEMALE	-0.009	-0.138^{**}	-0.010	-0.127^{***}	0.005	
	(35.02)	(33.29)	(34.56)	(23.84)	(32.81)	
WHITE	0.014	0.023	0.005	0.013	0.001	-0.000
	(36.29)	(32.29)	(34.37)	(26.31)	(31.26)	(31.15)
BLACK	0.043	0.073^{**}	0.046	0.062^{***}	0.049^{*}	0.045^{*}
	(33.54)	(37.53)	(33.19)	(26.99)	(31.47)	(31.54)
ASIAN	-0.021	-0.095	0.001	-0.040	-0.018	-0.031
	(38.92)	(41.41)	(33.85)	(23.97)	(37.59)	(37.97)
AMEIND	-0.097^{*}	-0.088	-0.097^{*}	-0.097^{*}	-0.100^{*}	-0.107^{*}
	(204.6)	(201.4)	(201.8)	(193.6)	(198.2)	(198.4)
POLITICAL	0.021	0.029	0.028	0.014		
	(11.93)	(11.08)	(11.63)	(10.30)		
REPUBLICAN	0.053	0.041	0.042			
	(74.41)	(72.43)	(71.35)			
INDEPENDENT	0.016	-0.031	-0.002			
	(29.70)	(29.95)	(25.63)			

SCHOOL	0.008	0.021	0.030		0.010	0.014
	(20.50)	(19.83)	(18.24)		(19.14)	(19.09)
ECONOMICS	-0.075	-0.015	-0.068		-0.065	-0.031
	(111.8)	(111.6)	(109.9)		(104.4)	(107.4)
SOCIAL	0.002	0.019	0.017		0.011	0.027
	(117.1)	(115.5)	(113.5)		(112.2)	(112.3)
MATH	-0.051	0.033	-0.049		-0.041	-0.030
	(111.6)	(110.5)	(109.7)		(107.3)	(106.7)
NATURAL	-0.004	0.076	0.011		0.007	0.014
	(104.7)	(103.5)	(102.4)		(99.87)	(99.01)
BUSINESS	-0.075	-0.017	-0.074		-0.072	-0.071
	(119.3)	(118.2)	(117.9)		(116.5)	(115.5)
OTHER	-0.074	0.027	-0.053		-0.066	-0.065
	(106.3)	(106.2)	(103.0)		(102.5)	(101.6)
HEALTH	-0.011		-0.014	0.023	0.001	0.006
	(27.45)		(27.08)	(17.68)	(22.08)	(17.85)
ENVIRONMENT	0.091^{*}		0.093^{**}		0.092^{**}	0.126^{***}
	(19.25)		(18.98)		(18.32)	(16.93)
ENERGY		0.049				-0.081
		(21.29)				(25.95)

SOCIETY		-0.106^{**}		-0.075^{*}			
		(17.75)		(14.14)			
Observations	11520	11520	11520	11520	11520	11520	11520
R^2 (Overall)	0.37	0.36	0.36	0.36	0.37	0.37	

Note: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

FIGURES

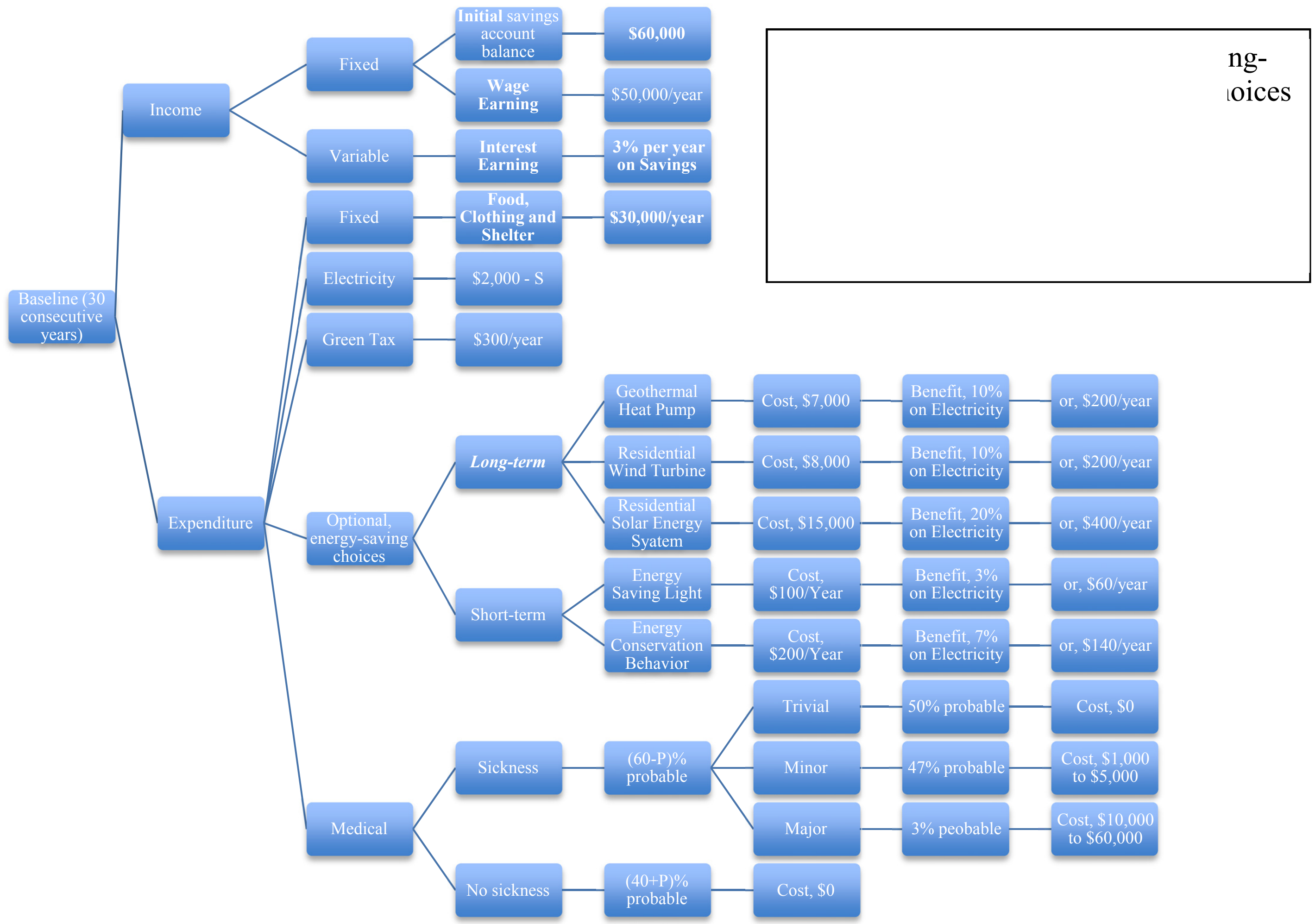

Figure 8: Experimental Design

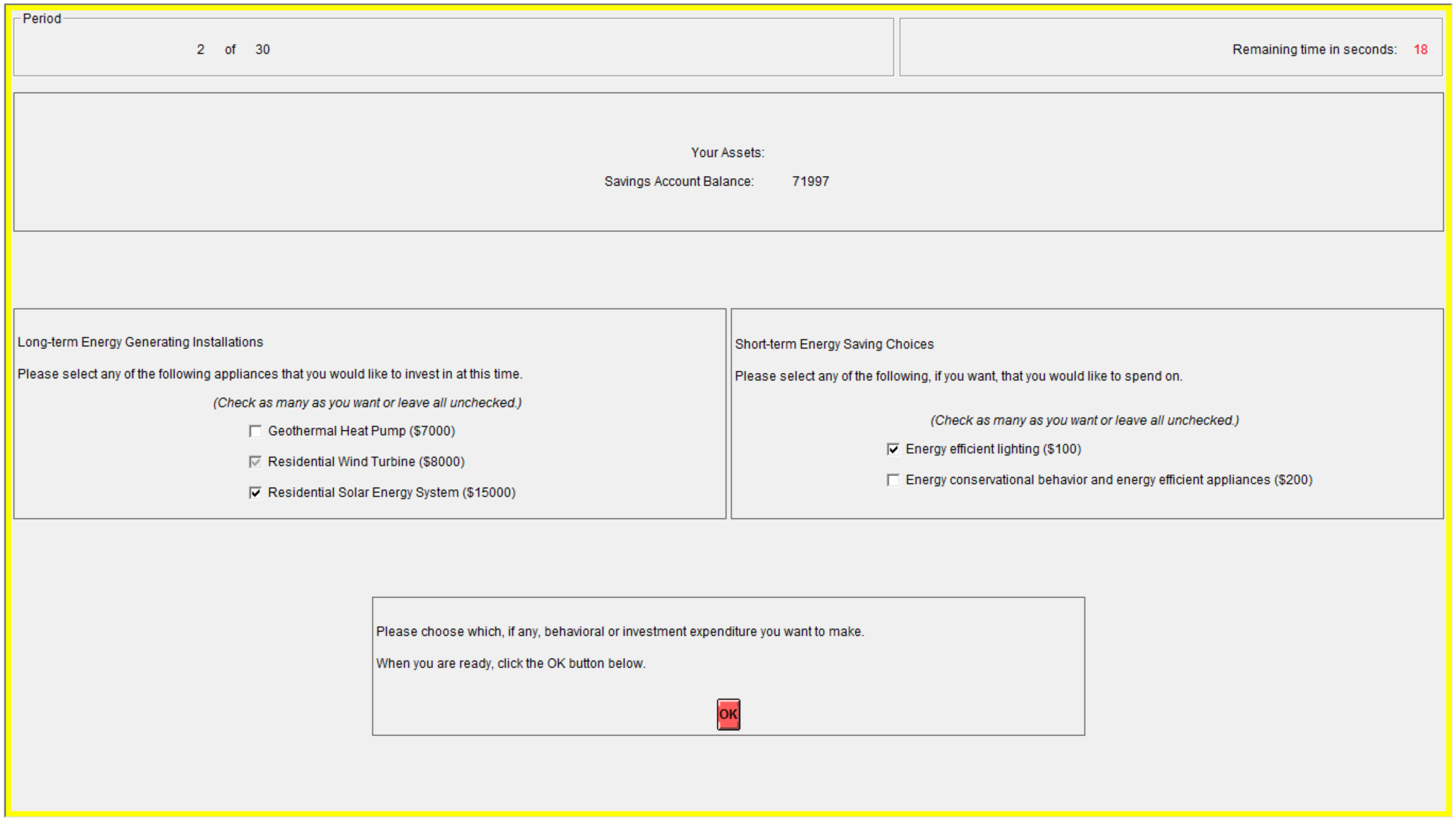

Figure 9: Energy saving choices during Experiment One and Experiment Three (Screenshot)

Note: The screenshot shows that it is the 2nd of 30 rounds. The subject has decided to invest in Solar Energy System this round. He also makes one short-term choice in the same round: Energy Efficient Lighting. Since the subject has already invested in Residential Wind Turbine in a previous round, it is grayed out. Once the subject chooses his desired investments, he clicks the "OK" button to find out the results of the round and move on to the next round.

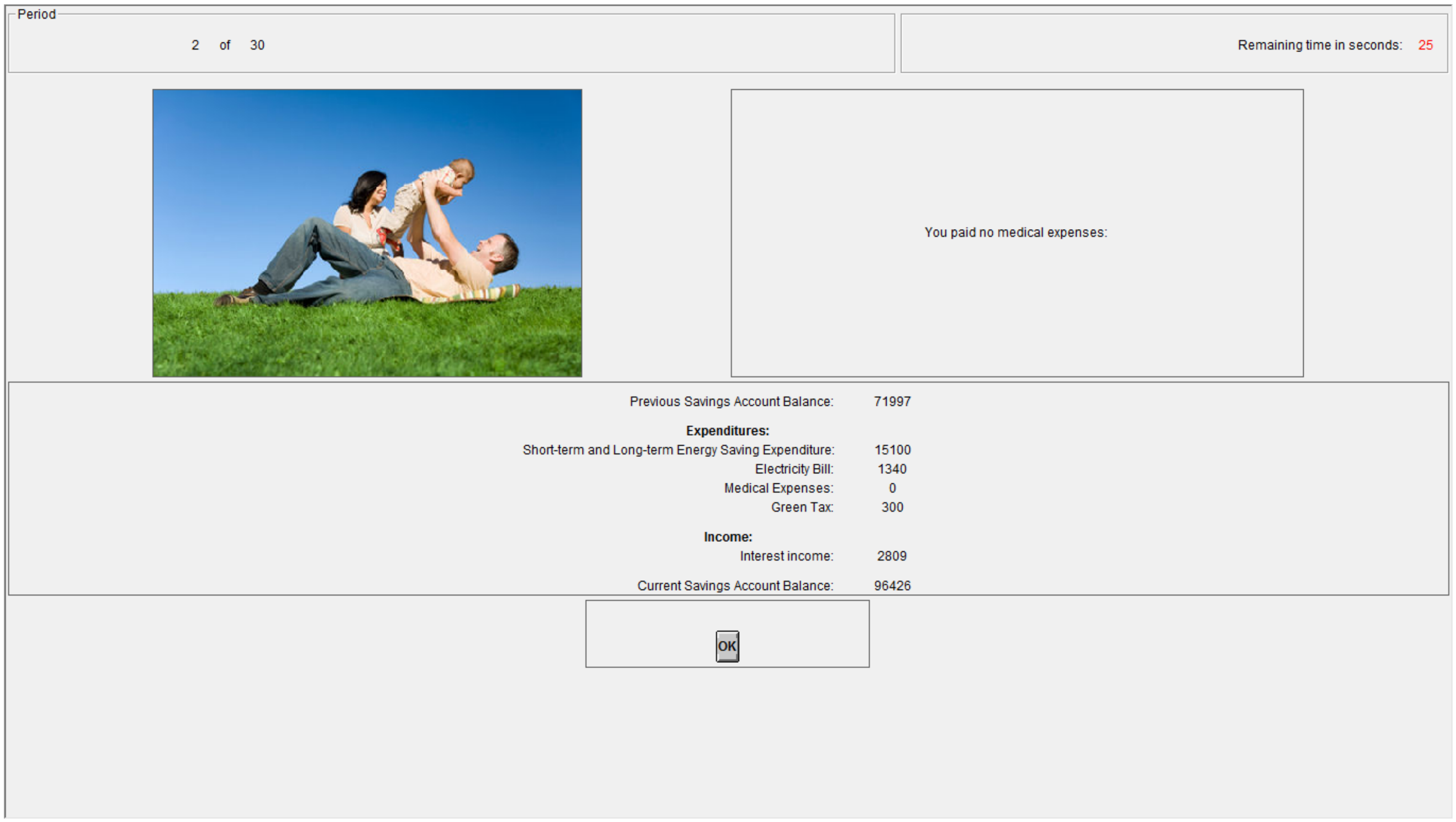

Figure 10: No medical expense during Experiment One (Screenshot)

Note: The subject has spent $15,100 on ESCST and ESC^{LT}. His electricity bill for the 2nd round is $1,340 and has also paid a Green Tax of $300. He has an interest earning of $2,809 and his new savings account balance is $96,426. He pays no medical expense.

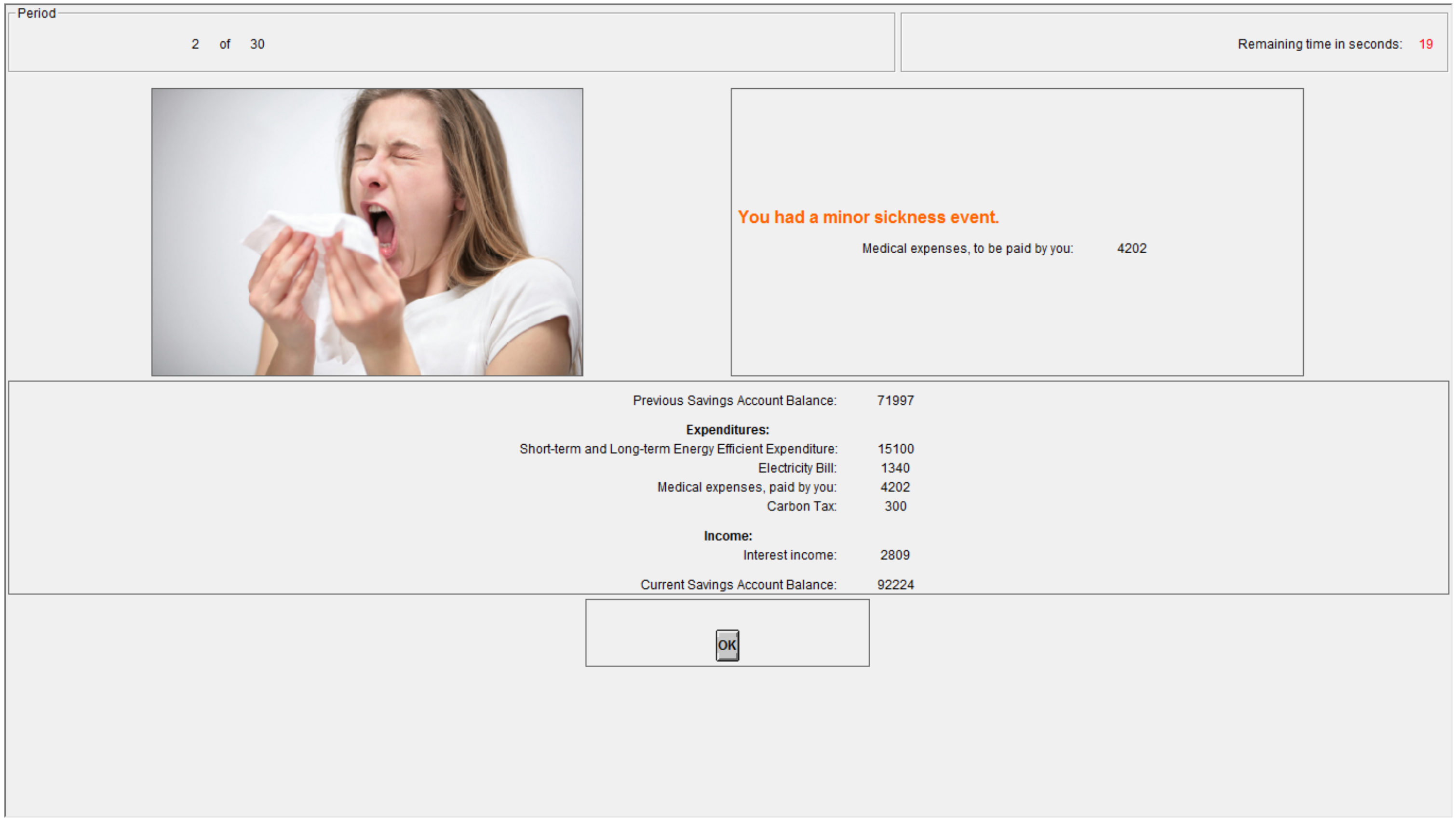

Figure 11: Minor medical expense during Experiment One (Screenshot)

Note: The subject has spent $15,100 on ESC^{ST} and ESC^{LT}. His electricity bill for the 2^{nd} round is $1,340 and has also paid a Green Tax of $300. He has an interest earning of $2,809 and his new savings account balance is $92,224. He pays a minor medical expense of $4,202.

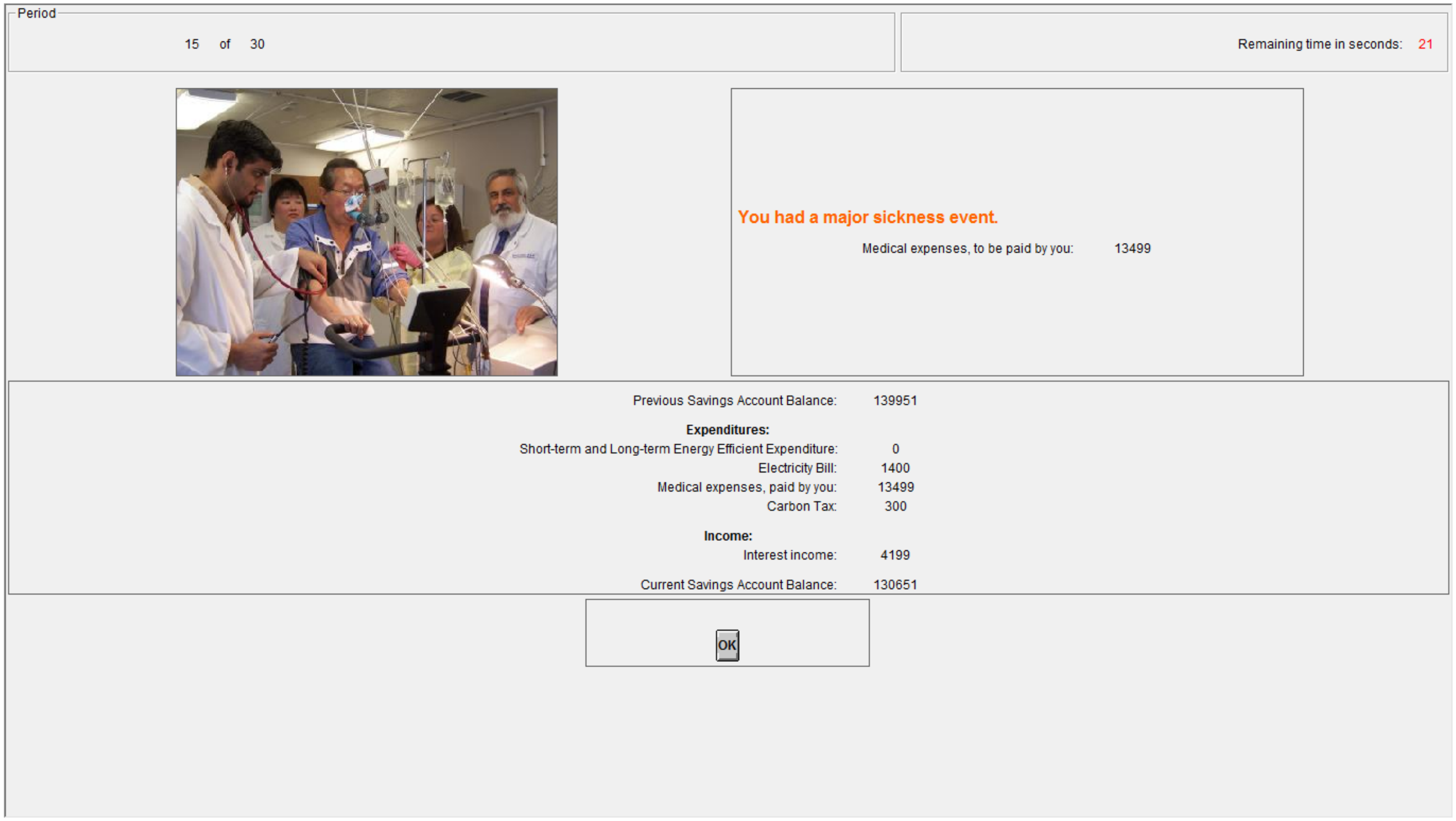

Figure 12: Major medical expense during Experiment One (Screenshot)

Note: The subject has not spent any money on ESCST and ESC^{LT}. His electricity bill for the 15th round is $1,400 and has also paid a Green Tax of $300. He has an interest earning of $4,199 and his new savings account balance is $130,651. He pays a major medical expense of $13,499.

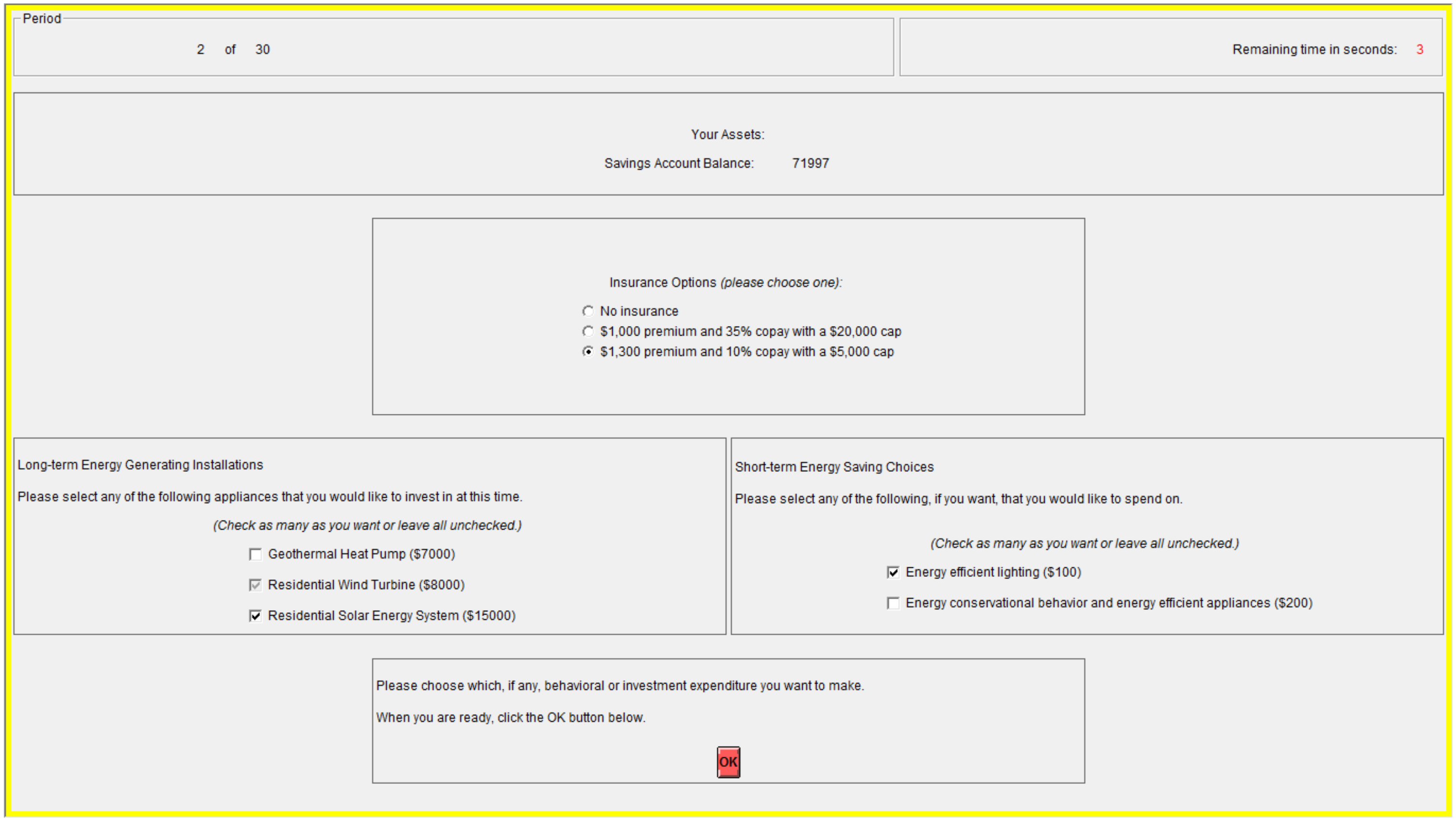

Figure 13: Energy saving choices during Experiment One and Experiment Three (Screenshot)

Note: The screenshot shows that it is the 2nd of 30 rounds. The subject has decided to invest in Solar Energy System this round. He also makes one short-term choice in the same round: Energy Efficient Lighting. Since the subject has already invested in Residential Wind Turbine in a previous round, it is grayed out. He has also selected the "$1,300 premium and 10% co-pay with a $5,000 cap" insurance policy. Once the subject chooses his desired investments, he clicks the "OK" button to find out the results of the round and move on to the next round.

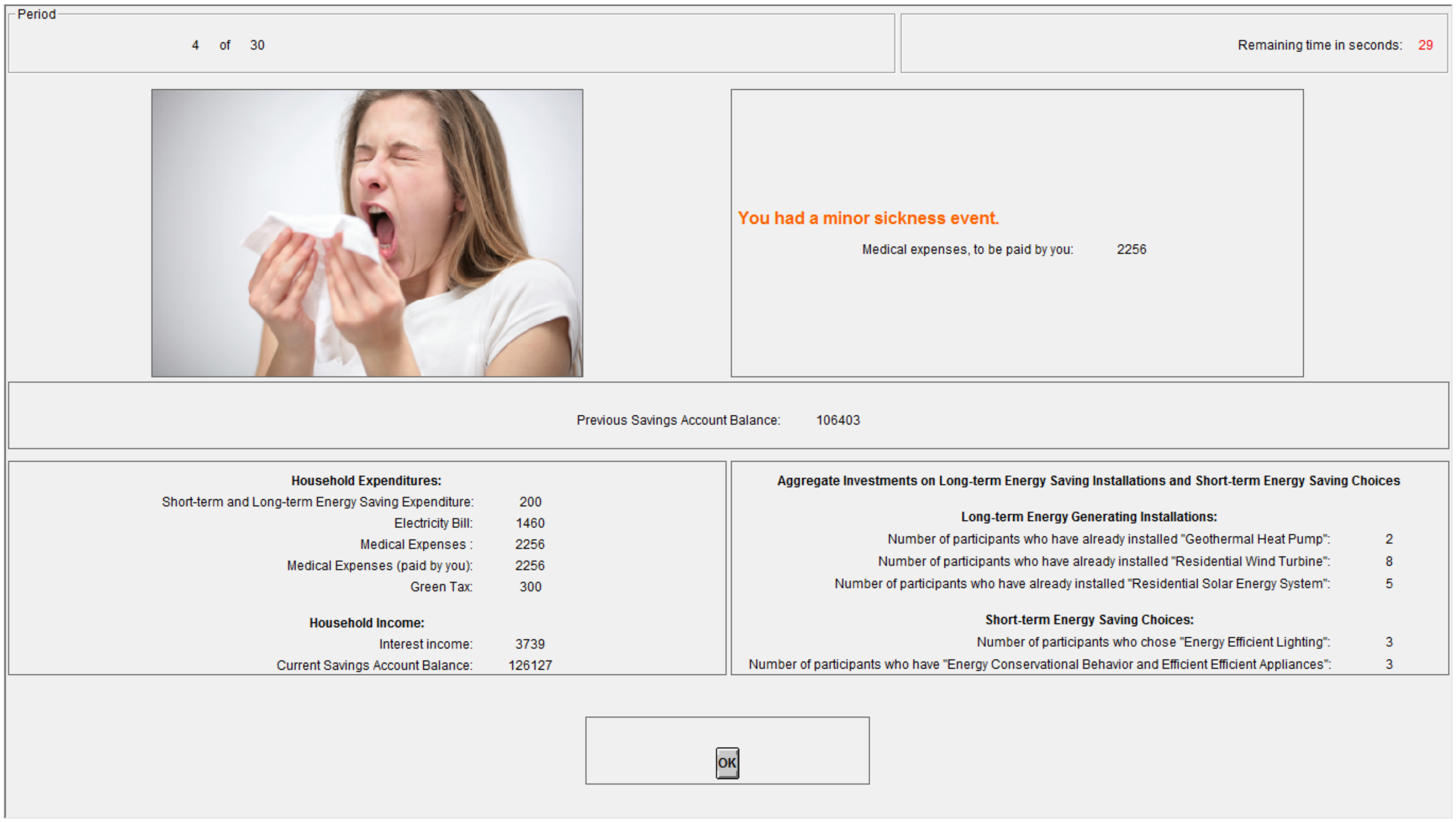

Figure 14: Minor medical expense during Experiment Three (Screenshot)

Note: The subject has spent \$200 on ESC^{ST} and ESC^{LT} in total. His electricity bill for the 4th round is \$1,460 and has also paid a Green Tax of \$300. He has an interest earning of \$3,739 and his new savings account balance is \$126,127. He pays a minor medical expense of \$2,256. It can be seen that among the 8 subjects, 2 have installed GHP, 8 have installed RWT, and 5 have installed RSES. For ESC^{ST}, 2 of the subjects have chosen EEL and 3 have selected ECB for that particular round.

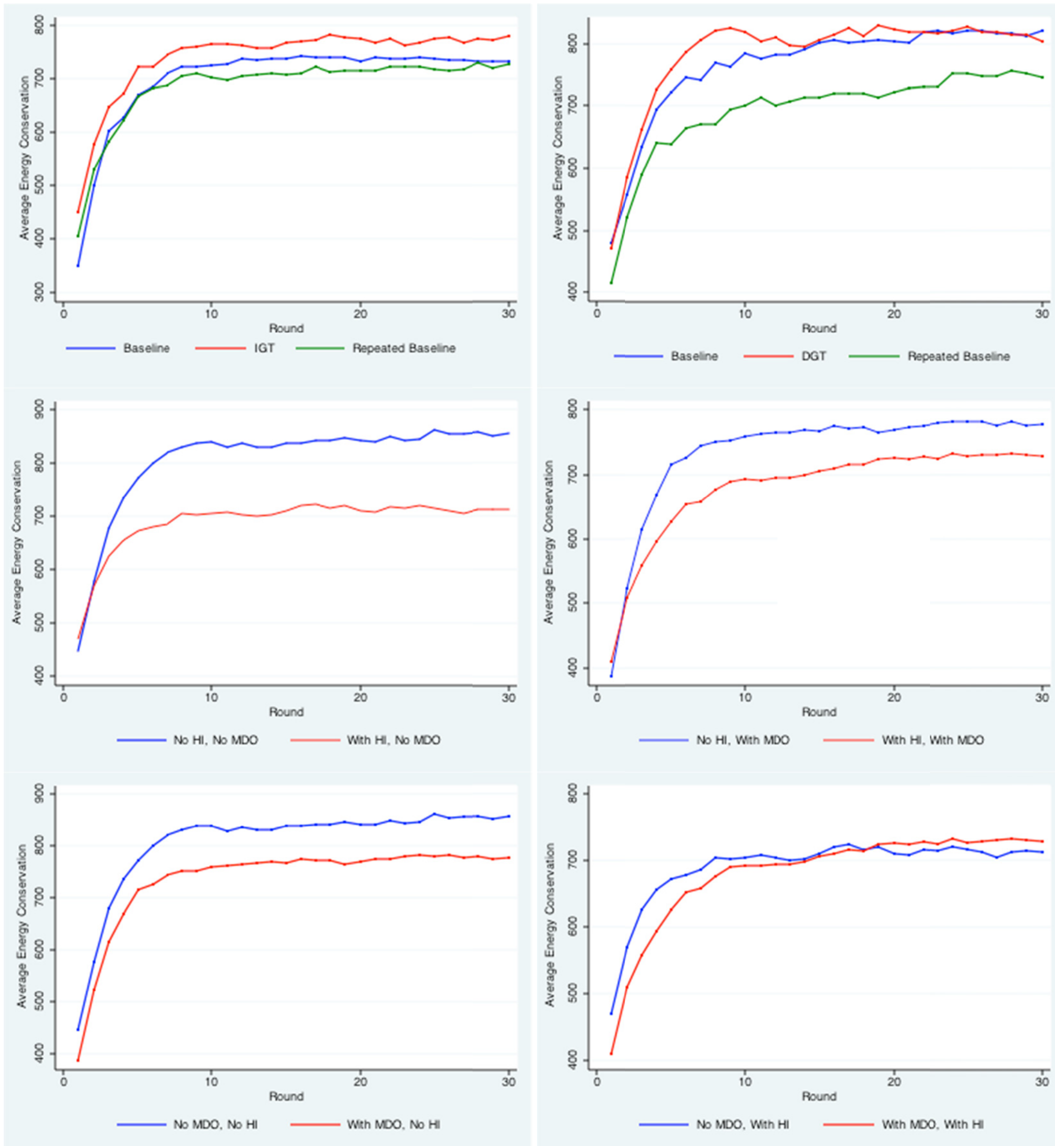

Figure 15: Average Energy Conservation over *ROUND*

Note: Average energy conservation (***CONSERVATION***) is plotted over 30 rounds (***ROUND***) on different criterions to reflect effectiveness of IGT (Increasing Green Tax, treatment), DGT (Decreasing Green Tax, treatment), Health Insurance (HI) with and without information and Information (MDO) with and without Health Insurance.

CHAPTER III:

UNDERSTANDING HOUSEHOLD PREFERENCES FOR HURRICANE RISK MITIGATION INFORMATION: EVIDENCE FROM SURVEY RESPONSES

1. INTRODUCTION

Catastrophic losses caused by hurricane related hazards have led to increasing calls for a shift in mitigation behavior. It is clearly evident that investment in natural hazard mitigation activities is highly efficient from the viewpoint of economic returns. For instance, the Multihazard Mitigation Council (2005) report shows that each dollar spent in hazard mitigation provides a return of $4 in terms of future net benefits to the society (Lindell and Prater 2000; Merrell et al. 2005). Public agencies are experimenting in designing innovative programs to encourage homeowners to adopt mitigation measures against coastal hazards risks. Better information about hurricane risk mitigation status (HRMS) of residential structures can motivate homeowners to undertake mitigation measures and to become effective stewards in developing resilient coastal communities (Thieken 2006; Siegrist and Gutscher 2008; Ge 2011).

Risk information is essential in informing the population living in hurricane prone areas (Crowther 2007). However, in many cases information is not easily available and households may have different preferences for seeking risk information (Englehardt 2002; Yokota and Thompson 2004; Weber and Siebenmorgen 2005). Being exposed to hurricane threats, people face difficult choices to make. Effective risk communication is at the heart of making efficient choices and the significance of effective hurricane risk communication is drawing more attention (National Science Board Report 2007). Social science research can elicit useful information to facilitate better risk communication to enable stakeholders make optimal choices. Communicating risk information to stakeholders can help the society efficiently organize risk-averting behavior (Mozumder et al. 2008).

For example, information regarding a residential structure's capacity to stand against hurricanes of different strength can affect mitigation choices in different ways (Santella et al. 2010). A host of other factors e.g., available resources, financial incentives for mitigation measures, physical location, and a variety of household characteristics (e.g., risk perception, past exposure (Khan and Suaris 1994), education (Lindell and Hwang 2008), number of children (Trumbo 2011) and elderly people at home, insurance status and structural characteristics of the living place) may influence the demand for risk information that eventually affect mitigation behavior. Against this backdrop, I examine survey responses in relation to a novel program; My Safe Florida Home (MSFH) that is designed to encourage residents to adopt mitigation measures to reduced damages caused by hurricane and other windstorms.[10]

An important policy question is how people respond to these types of programs developed to provide risk information and promote mitigation. Who are likely to respond more based on the implicit and explicit cost and benefit they face? Since risk information is critical in adopting mitigation measures, I analyze household willingness to allow a state-certified inspector to evaluate the hurricane risk mitigation status (HRMS) of the

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[10] The State of Florida has recently initiated the My Safe Florida Home (MSFH) program which provides a free inspection to evaluate the hurricane risk mitigation status (HRMS) of residential structure and a matching grant (up to $5000) for retrofitting suggested by a State certified inspector (visit http://www.mysafefloridahome.com for further details about this program).

residential structure they live in (a core component of the MSFH program). I identify major drivers of household preference for this pertinent risk information. I expect insights from this analysis may provide helpful inputs in designing efficient and cost-effective public policy to influence household's mitigation behavior in a desired direction.

2. LITERATURE REVIEW

Kunreuther et al. (2004) highlighted the need for research that focus on what type of information is effective to stakeholders to ensure the optimal level of investment in risk mitigation measures. They also report evidence that individuals often tend to under-invest in self-protective mitigation measures when such measures are cost-effective but over-invest when they are ineffective. Variety of evidence suggests that people fail to recognize or act well against low probability, high-consequence events such as hurricanes even though it is against the prediction made by the expected utility theory. Information plays a crucial role in explaining this type of behavior since critical information in establishing the link between risk perception and risk mitigation behavior is often missing.

Information provision is emerging as a common policy tool in environmental risk management (Petrakis et al. 2005; Tietenberg and Wheeler 2001). Better risk information can have efficiency-enhancing impacts in a variety of natural resource management contexts (Costello et al. 1998; Bontems and Thomas 2000). Communicating risk information to stakeholders in natural hazard mitigation planning can also increase total mitigation efforts and help set priority for further policy intervention. However, the targeted audience of natural hazard mitigation policy is not a simple homogeneous group to comply with public policy programs of hazard mitigation. Rather there exists considerable extent of heterogeneity in terms of risk perception, ability to respond and some other salient factors (Wilson et al. 2002).

In documenting heterogeneity of behavior related to hurricane related hazards, for instance, Peacock et al. conducted a survey to explore how various factors affect hurricane risk perceptions of single-family homeowners in Florida (Peacock et al. 2005). Findings (conducted on 1260 households residing in single-family owner occupied detached homes) indicate that experience, knowledge about the hurricanes and location of the home significantly affect hurricane risk perception. In another study, Peacock (2003) reported survey findings (a phone survey on 1533 homeowners) of single-family homeowners to assess hurricane mitigation status and found that year of residency and income had a positive effect but ethnicity (black) had a negative effect on adopting hurricane mitigation measures (e.g., shutter usage, envelope coverage).

Smith et al. (2006) investigated the role of ethnic, demographic and economic factors in coping with damages caused by a hurricane in Miami and found that income played a major role in the post disaster adjustment process more than other factors (e.g., ethnicity). Depending on income people either moved out or built their homes stronger and bought insurance to reduce the damage. Simmons et al. (2002) used data from Multiple Listing Service to investigate the role of self-insurance and self-protective mitigation measures in preventing damages from hurricanes on the resale value of single-family homes. They found that the structural integrity index (SII) composed of topographical location, structural characteristics and architectural features were positively correlated with the resale value of single-family homes.

Prater and Lindell (2000) focus on political aspects of adopting mitigation measures and conclude that ex-ante natural hazard mitigation programs are not very popular political agenda due to their long-term uncertain benefits. Investing funds in education, crime reduction, urbanization etc. that generate direct benefits are considered politically more rewarding compared to promoting mitigation. Despite the State of Florida has recently initiated a novel and innovative program (My Safe Florida Home, MSFH), which is designed to encourage residents to adopt mitigation measures and reduce damages caused by hurricane related hazards.

The State of Florida Legislature created the MSFH program in 2006 through the enactment of Section 215.5586, Florida Statutes (My Safe Florida Home 2008a). The program is designed to offer low-income homeowners the opportunity to strengthen and retrofit their homes against coastal hazards. The MSFA program works in collaboration with local governments and a volunteer organization to offer free home inspection to eligible homeowners (Volunteer Florida Foundation 2008). The program established by the Department of Financial Services (DFS) will end on June 30, 2009.[11] There are certain eligibility criteria to participate in the program. A Florida resident, who owns a detached single-family home with an insured value of $500,000 or less and built prior to March 1, 2002, is eligible for free inspection. If a homeowner is not eligible for the program, he/she can pay a cost ($150) to get the home inspection done. The inspection report documents the steps that are essential to increase the resistance of a home against

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11 A total of $250 million fund is allocated to provide at least 400,000 inspections and 35,000 grants.[32] Based on the data collected from the public records of the My Safe Florida Home program (by April 2008), 65,536 applicants completed home inspections and 20,699 was approved (with a 31.6 % approval rate) for receiving grant assistance for mitigation.

hurricane damage, explaining and prioritizing seven home retrofits. The inspector also provides the estimated cost for improvements and potential insurance discounts available for those home improvements (My Safe Florida Home 2008).

Different types of benefits are attached to the home inspection report. First, eligible applicants with home inspections approved by the DFS can apply for a matching grant up to $5,000 to cover the expenses for specific mitigation measures. To be eligible for the grant, the inspections need to be conducted by an inspector certified by the DFS. Approved residents are provided with one year of time to complete the recommended improvements. There are seven specific categories of hurricane damage mitigation improvements, which are covered by this program. These include upgrading the strength of roof deck attachment, installation of the secondary roof water barrier, improvement in the roof covering from the wind damage, bracing gable end walls, reinforcement of roof-to-wall, installation storm shutters to protect window openings and increasing the strength of the exterior doors. Second, homeowners may qualify for insurance discounts. The mitigation form approved by the certified MSFH inspector sent along with the inspection report can be used as a proof of specific mitigation measures adopted to qualify for insurance discounts. Discounts vary depending on the criteria set by the insurance companies and improvements made.[12]

Certain restrictions apply to participate in the program. Reimbursement of expenses also depends on homeowner's income. The grant reimbursement is 100% of the actual

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[12] DFS has also recently developed a no interest loan program to encourage that involve private lending agencies in providing loans to homeowners of site-built property to cover the cost of mitigation measures. The loan is up to $5,000 for three years to homeowners and DFS will pay the market rate interest on the loan.

costs (not more than $5000) if applicant is a low-income homeowner (80% or less than average household income of the county) and 50% if non-low income homeowner. A valid homestead exemption (authorized by the local property appraiser's office) is required to be eligible for receiving the grant money.[13] The information provided in the application for grant and in the inspection report both are considered as public records and can be disclosed to insurance carriers and others.

Against this backdrop, no prior study in coastal hazard mitigation context investigates household's preference for risk information regarding hurricane risk mitigation status (HRMS) of the residential structure they live in. To fill this gap, I develop an analytical framework for analyzing household response in receiving this type of pertinent risk information. The analytical framework is used to motivate an empirical analysis based on a household survey. Using both single equation (probit) and joint equation (bivariate probit) probability models, I investigate the factors that affect household demand for information regarding hurricane risk mitigation status (HRMS).

3. ANALYTICAL FRAMEWORK

I have used a utility-theoretic framework to gain insights on household willingness to allow a state-certified inspector to provide information about the hurricane risk mitigation status (HRMS) of their homes. Using a flexible random utility model (RUM), I investigate households' preference for hurricane risk mitigation information. Self-protective mitigation behavior of households', is a multi-dimensional decision variable.

[13] In Florida, the homestead exemption proof in each county is given by the local property appraiser's office each year, which shows an exemption of at least $25,000 of appraised home value for property tax (see www.mysafefloridahome.com for further details).

To begin with, let the indirect utility function of a household, living in a coastal hazard prone area, is written as follows.

$$U(I, HRMS, F) \tag{1}$$

That is, utility of a family is considered to be a function of family income (*I*), desire and initiative to seek hurricane risk information through MSFH inspection (*HRMS*), and a set of socio-demographic characteristics (*F*). As in the study, households are asked whether they will like to have a free inspection, or not, under the MSFH program; HRMS is treated as a dichotomous variable. Households can either aware of their hurricane risk mitigation status (*HRMS* = 1) through opting for a free house inspection, or may not (*HRMS* = 0).

A household is supposed to avoid such an inspection, if and only if the opportunity cost of inspection, CI, is offsetting enough. That is, a household intends to avoid the MSFH inspection if the following condition satisfies.

$$U(I, HRMS = 0, F) > U(I - CI, HRMS = 1, F) \tag{2}$$

Vice versa, the household will apply for the free MSFH inspection, if

$$U(I, HRMS = 0, F) < U(I - CI, HRMS = 1, F) \tag{3}$$

As hurricane-strike on a residential structure is an uncertain incident, utility levels of households' correspond to both a deterministic (V), and a stochastic component (ε). That is,

$$U = V + \varepsilon \tag{4}$$

Due to potential protection measures, stochastic component of utility differs with and without risk information, and therefore with an MSFH inspection. If we suppose that the indirect utility function of the household is linear in nature, the utility level of the household in concern can be represented as following.[14]

$$U = \begin{cases} \delta_0 I + \gamma_0 F + \varepsilon_0 & if \quad HRMS = 0 \\ \delta_1 (I - CI) + \gamma_1 F + \varepsilon_1 & if \quad HRMS = 1 \end{cases} \tag{5}$$

In the expression above, δ and γ have been used to represent the coefficients[15] of earnings to be spend, and characteristics of a households, respectively. Therefore, probability that a household asks for an inspection can be expressed as follows.

$$\begin{aligned} P[HRMS = 1] &= [U(I - CI, HRMS = 1, F) > U(I, HRMS = 0, F)] \\ &= P[(\delta_1 - \delta_0)I - \delta_1 CI + (\gamma_1 - \gamma_0)F > (\varepsilon_0 - \varepsilon_1)] \\ &= P[m > E] = \Phi(m) \end{aligned} \tag{6}$$

In the expression above $(\delta_1 - \delta_0)I - \delta_1 CI + (\gamma_1 - \gamma_0)F = m$, and $\varepsilon_0 - \varepsilon_1 = E$.

We suppose that E is independently and identically distributed (iid), and Φ is a standard normal cumulative density function (CDF). The above model outlined is capable of empirically analyze the choices made by households, whether to allow (or not to) the home inspection under MSFH, and obtain HRMS. As the home inspection is provided free for eligible residents, the cost of the inspection (*CI*) implies the overall opportunity cost of allowing the inspection. A household never asks for the inspection, if it does not increase the utility level. That is, if the household already knows the risk information or the disutility caused by the inspection exceeds the gain in utility from knowing the risk

[14] We have used $\varepsilon = \varepsilon_0$ when *HRMS*=0, and $\varepsilon = \varepsilon_1$ when *HRMS*=1.

[15] δ and γ are specific to household's preference for inspection, and therefore are subscribed with preference status of the concerned household with MSFH inspection.

information, the household rationally chooses not to opt for the MSFH inspection. I have analyzed the above, based on a household survey explained in the next section.

4. DATA DESCRIPTION

The International Hurricane Research Center at the Florida International University (Miami, Florida) conducts an annual survey to gather information in relation to Florida residents' hurricane preparedness, each year at the beginning of the hurricane season. In 2007, they conducted a phone survey (July 7-15, 2007), and asked respondents a number of questions concerning the My Safe Florida Home (MSFH) program. Using a random sample of registered voters living in Florida, the phone survey produced a total of 800 complete adult household responses. Along with a host of socio-demographic information, the survey asked for households' preference for hurricane preparedness, and mitigation responses.

The responses have been summarized in Table 8, when Table 9 explains questions asked to particular responses. It is evident from Table 9 that thirty percent of the respondents live in an evacuation zone. Eighty eight percent respondents have insurance to protect from damages to the residential structure they live in, and six percent of the households live in a manufactured or mobile home. In the complete sample, almost fifty six percent respondents feel extremely, or somewhat vulnerable, that they may suffer from damages caused by hurricane related hazards. Forty percent respondents report that household members in their family have been living in a physically damaged home caused by hurricane related hazards. As observed in Table 8, ninety six percent of the respondents have experience with tropical storms or hurricanes, where more than fifty six percent had either major or moderate damages, and eighty percent have suffered wind related damages (e.g., wind debris breaking doors, windows and wind damaging the roof).

More than fifty percent respondents are aware of different types of discounts on adoption of hurricane risk mitigation measures (e.g., using window shutters, reinforcing roof by improved bracing and sheathing, reinforcing garage doors etc.). In a serious hurricane situation, eighty five percent of the respondents report that they have a plan to act. Around fifty eight percent respondents are quite certain that they have all necessary information to protect their lives and homes from hurricane related damages. Of particular interest for this analysis, more than sixty seven percent respondents confer positive respond that they will allow a state-certified inspector into their home to evaluate the hurricane risk mitigation status (HRMS) for free. Although, only twenty nine percent of the respondents are aware of free home inspections and monetary assistance under the MSFH program.

Thirty nine percent of the respondents are male, and average size of the household is 3.19. Fifty five percent respondents have children (under 12 years), and/or senior citizen (above 65 years) living in the house. The annual income of the median respondent falls in the band of 50-75 thousands. By education, the median respondent is a college graduate. Now, let us discuss the estimation method in the next section.

5. EMRIRICAL SPECIFICATION

In studies of social science, as economics, probit model is popular as regression analysis for modeling categorical dependent variables. Therefore, the first analyzing tool I have used is the probit estimation technique. The suitability of probit model can be explained in application of the latent variable U. Often in social sciences, the dependent variable (U) is continuous in nature, but not observable. Instead, it results determining the outcome that is evident (*Inspection* = 0 or 1).[16] As explained in equation (3), different utility levels corresponding to the decision of the respondent whether to allow a MSFH inspection or not, therefore determines the value of the outcome or the dependent variable (*Inspection*).

In the probit estimation, I suppose that U follows a standard normal distribution. In general term, the probit estimation model is of the following form.

$$U + \beta X + \varepsilon \tag{7}$$

X and β represent vectors of independent and socio-demographic variables of respective household, and corresponding coefficients. Assuming random sampling, probit estimation method maximizes the following likelihood function (L).

$$L = \sum (Inspection) \ln[\Phi(U)] + \sum (1 - Inspection) \ln[1 - \Phi(U)] \tag{8}$$

I, though, suspect the issue of selectivity bias due to non-random distribution of some explanatory variables across the sample, awareness of the MSFH program (*Aware*) and perception of vulnerability to hurricanes (*Vulnerable*). There are individual and household level unobserved factors, and being aware about the MSFH program or feeling vulnerable to hurricane damages can result choice of MSFH inspection, as they are two interrelated decisions of a single respondent. The other estimation method, I have applied, is therefore the bivariate probit approach that addresses selectivity bias with two of the explanatory variables, *Aware* and *Vulnerable*.[17] The bivariate probit model is a

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[16] Please see Hausman and Wise (1978) and Cohen (2003) for details.

[17] Please see Staton (2006) for detailed application of bivariate probit approach.

joint estimation technique; where probability of allowing a MSFH inspection (*Inspection*) to evaluate hurricane mitigation status and, probability of being aware of the MSFH program (*Aware*) or feeling vulnerable of Hurricane damages (*Vulnerable*), are estimated together.

Explaining the estimation technique, let Y is another latent variable for *Aware* or *Vulnerable*. Then,

$$U = \beta X + \varepsilon \tag{9}$$

$$Y = \alpha Z + \eta \tag{10}$$

X and Z, again, represent vectors of independent and socio-demographic variables of respective household and corresponding coefficients, in relation to being aware of the MSFH program or feeling vulnerable from hurricane damages. The corresponding coefficients are β and α. Following Greene (1998, 2003), the errors ε and η follow a bivariate normal distribution (BVN) with mean zero variance one. The correlation coefficient (ρ) between the error terms is not zero, or $\rho = \text{cov}(\varepsilon, \eta)$.

6. RESULT

In Table 10, probit probability models show that the coefficient of *Insurance* is positive and highly significant (at 1% levels in Models 1 to 4). That is if the respondent carries an insurance to protect damages to the residential structure (*Insurance*), he/she is more willing to allow home inspection (in all four models in Table 10). The finding indicates that households who have insurance see a higher incentive to obtain the risk information as they can use the inspection report to claim insurance rebates from their insurance companies. Next, the coefficient of *Damage* is positive and significant at 1%

levels in all four models. This implies that experience with physical damages to home, from hurricane related hazards in the past, significantly increases the probability of allowing a home inspection. In consistence to earlier studies, the probability of allowing a home inspection is expected to increase with perception of vulnerability to hurricane damages (*Vulnerability*) at 5% level of significance (Models 1-4, Table 10). For instance, Mozumder et al. (2008) found that higher perception of risk leads to a higher demand for risk information related to wildfires in an urban wild-land interface. Alongside, prior experience (*Exposure*) with a hurricane or a tropical storm (not necessarily experienced physical damages) is also seen to be positively associated with the higher probability of allowing inspection (the coefficient of *Exposure* is positive and significant at 5% levels in Models 1 to 4).

Different household characteristics are also found to affect the willingness to allow a home inspection. Households with more members are less likely to allow a home inspection since the coefficient of *Members* is negative and significant (at 1% and 5% levels) in three out of four models (Models 2, 3 and 4). Households with more members face a higher opportunity cost to allow the inspection, as it will require more adjustments to be made in their usual lifestyle.[18] The coefficient of *Income* is not statistically significant in any of the two models (Model 2 and 3). The negative sign of its coefficient (robust in all two models) imply that households with lower income may utilize the opportunity of free home inspection. The coefficient of *Education* is also negative and

[18] This is also consistent with the negative coefficient of the variable *Dependent* in Model 4 (though not statistically significant). Dependent is a dummy variable, which controls for children (under 12 years) and/or seniors (above 65 years) living in the household. These households also may face a disproportionately higher opportunity cost in making adjustments to allow a home inspection.

significant (Model 1 and 4) indicating that highly educated households (who are often high income earners) are less likely to respond this program. These findings provide some evidence of the program's effectiveness since MSFH program is designed to help low income households to adopt hurricane risk mitigation measures (Florida Association of Insurance Agents 2007). Regarding other control variables, the coefficient of *Plan* (Model 2, 3, and 4) and *Evacuation* (Model 4) are positive but not statistically significant. Households living in evacuation zones are tied up with a higher level of location-specific costal hazard risk (because of the danger of storm surge) may feel a higher need of the risk information. Households who have a plan to act on as the hurricane approaches may also feel a higher need of risk information as it helps to take ex-ante mitigation measures to reduce the risk. However, the coefficient of *Information* is negative (not statistically significant in Model 3 and 4) may imply that this group of households may be well informed of HRMS and so may be less willing to allow inspection.

The sign of the coefficient of *Mobilehome* is negative and significant at 5% level, implying residents, living in a manufactured or mobile home, are less willing to allow a home inspection (Models 1, 2, 3, and 4). Households living in mobile or manufactured homes may be well aware that these residential structures are highly prone to hurricane winds and may not want to receive a further confirmation through an additional piece of risk information. The coefficient of *Aware* is not significant and is also inconsistent in terms of its sign (Models 2, 3, and 4). Based on these probit estimates, thus it may imply that awareness about the MSFH program does not systematically affect the household's willingness to allow a home inspection.

The MSFH program awareness may be prone to selectivity bias leading to biased probability estimates in probit models reported in Table 3. Selectivity bias may arise as a consequence of non-random distribution of awareness regarding MSFH program. In Table 12, I have reported the estimated probability of allowing a free home inspection using bivariate probit models which allows awareness regarding MSFH program (*Aware*) to be explained by a host of factors in a separate equation. Table 12 shows the estimated probability of being aware of My Safe Florida Home (MSFH) program. The coefficient of *Insurance* is positive and significant in all four models. The coefficient of *Damage* is positive, but insignificant (in Model 5 and 8). Households who consider that they are certain that they have all necessary information are more likely to be aware of the MSFH program since the coefficient of *Information* is positive and significant at 5% level (in Models 5, 7 and 8). Households that live in a mobile or manufactured home are more likely to be aware of the MSFH program (the coefficient of *Mobilehome* is positive and significant at 10% significance level in Model 8). Regarding other control variables, household size (*Members*) is negatively associated with awareness of MSFH program (Models 7).

Table 12 also documents the factors that significantly affect the probability of allowing a home inspection to obtain HRMS inspection. In consistence with the probit model estimation results, households carrying insurance (*Insurance*) are more likely to allow a free inspection. Households can realize the potential benefit of the HRMS inspection report to claim insurance discounts. Consistent with probit models, the coefficient of *Damage* is positive and highly significant (at 1% levels in Models 5, 6, 7, and 8) indicating that households, who suffered physical damages in the past, are more likely to allow inspection. A higher perception of vulnerability to hurricane induced damages also leads to increase the willingness to allow a home inspection since the coefficient of *Vulnerability* is positive and significant (at 5% levels in Models 5 to 8, Table 12) implying that the perception of vulnerability to damages by hurricane related hazards leads to increased probability of allowing a home inspection. The coefficient of *Exposure* is also positive and significant (at 5% levels, Models 5 to 8). That is, prior experience with a tropical storm and/or a hurricane positively affects the probability of allowing a home inspection. The coefficient of *Residency* is negative and significant (at 5% levels in Models 5 to 8). The finding implies that the number of years a household living in Florida (as a permanent resident) negatively affects the probability of allowing inspection. Mozumder et al. (2008) also find that households lived longer in a hazard prone area are less willing to positively respond to seek hazard related risk information.

Regarding household-specific characteristics, the coefficient of *Income* is negative and insignificant (in Models 6 and 7). As seen before (in Table 10), household size negatively affects the probability of allowing inspection since the coefficient of *Members* is negative and significant in Models 6, 7 and 8. The coefficient of *Mobilehome* is also negative and significant (at 5% levels in Models 5 to 8) implying that households living in a mobile or manufactured home are less likely to allow a home inspection. Regarding other control factors; such as presence of children and/or senior members (*Dependent*), location of household in an evacuation zone (*Evacuation*) and gender of the respondent (*Gender*) do not seem to affect the probability of allowing the inspection. Overall these results are consistent with findings from probit models reported in Table 10.

Similar to awareness regarding the MSFH program, I also consider that the perception of vulnerability to damages caused by hurricane related hazards (*Vulnerability*) might also be distributed in a non-random fashion across the sample (which can potentially cause selectivity bias). In Table 14, I report estimated probability of allowing free inspection by using bivariate probit models, allowing *Vulnerability* to be explained by a host of factors in a separate equation. A number of factors explain *Vulnerability*. The coefficients of *Damage*, *Exposure* and *Evacuation* are positive and highly significant at 1% levels in Models 9 to 12 implying that physical damages caused by hurricane related hazards, prior experience with a tropical storm and/or a hurricane and living in an evacuation zone significantly increase the perception of vulnerability. The coefficient of *Plan* is negative and significant (Model 10) implying that households with a plan feel less vulnerable. The coefficient of *Information* is negative and significant (at 1% level in Models 11 and 12). Therefore households who think that they have all necessary information feel less vulnerable and avoid the HRMS inspection. The coefficient of *Residency* is negative and significant (at 5% levels in Models 11 and 12) implying that the number of years a household living in Florida (as a permanent resident) negatively affects the perception of vulnerability. Male respondents are less likely to reporting vulnerable to damages (the coefficient of *Gender* is negative and significant at 5% levels in Models 11 and 12). Other common control variables, such as *Education* and *Income*, do not seem to affect the perception of vulnerability. The coefficient of *Mobilehome* is positive but not significant implying that households living in mobile or manufactured homes do not feel more vulnerable.

Results reported in Table 14 also show the factors affecting the probability of allowing inspection (*Inspection*) when the perception of vulnerability (*Vulnerability*) is to be explained by a host of relevant factors. Consistent with results reported in Table 10 and 12, the coefficients of *Insurance*, *Damage* and *Exposure* are positive and significant at (at 1% to 5% levels) in Models 9 to 12. As seen before (in Tables 3 and 5), years of residency in Florida (*Residency*), living in a mobile or manufactured home (*Mobilehome*) and household size (*Members*) negatively affects the probability of allowing a home inspection (see Models 9 to 12). *Income* tends to be insignificant, and the coefficient of *Education* is negative, and significant only in Model 9. Regarding other control factors such as *Dependent*, *Evacuation* and *Gender* do not seem to effect on willingness to allow inspection (see Models 12). Overall results reported here from probit and bivariate models (Table 10, 12 and 14) are largely consistent.

Tables 11, 13, and 15 report the marginal effects of the corresponding coefficients reported in Tables 10, 12 and 14. For bivariate probit models, marginal effects refers to the impact of a corresponding variable to the probability of allowing inspection conditional on the situation that a household is aware or not (in Models 5-8), and conditional on the situation that a household feel vulnerable or not to hurricane related damages (in Models 9-12). Considering statistically significant components in Tables 4, 6, and 8, *Insurance* increases the probability of allowing inspection by 5-21% based on different model specifications. Among other major drivers, *Damage* (by 4-23%)[19], *Exposure* (7-34%) and *Vulnerability* (2-9%) also significantly increase probability of

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[19] Though, if the respondent seems not to feel vulnerable or while *Vulnerability*=0, increase in damages (*Damage*) reduces probability of allowing inspection by 5-8% at 1% significant level (from Table 15).

allowing inspection. *Residency* (by 1-5%) and *Mobilehome* (by 1-19%), reduces the probability of allowing inspection. Household-specific factors like *Members*, *Income* (though not so robust), *Education* and *Gender* tend to reduce the probability of allowing inspection. The role of *Informatio*n is not consistent as the sign of its marginal effects changes across specifications. A similar case is evident for *Aware* (not significant) implying that roles of these factors are not robust across different models.

7. CONCLUSION

Despite the fact, that allocating public funds to promote ex-ante natural hazard mitigation measures is not a very popular political agenda (Prater and Lindell 2000), the State of Florida has initiated My Safe Florida Home to encourage mitigation. To promote preparedness and mitigation, the MSFH program is designed to provide free risk information (HRMS) and subsequent grant assistance for eligible households living in hurricane prone areas in Florida. Since there is a wide range of heterogeneity exists in terms of households' risk perception, ability to respond and other salient factors (Wilson 2002), detailed analysis of household behavior in response to a program promoting mitigation can provide useful inputs. Risk information is critical to adopting mitigation measures; and underlying costs and benefits (implicit and explicit) to seeking information influences a household's choice for risk information. Consistent with this line of argument, this study identifies major drivers of household preference for allowing a free inspection to receive pertinent risk mitigation information (HRMS), which is tied up with further possible benefits (grant assistance, insurance rebates). Based on a variety of empirical specifications, the analysis reveals that a household having insurance to protect damages to the residential structure is more likely to allow inspection for obtaining

HRMS. Households who feel vulnerable to physical damages are more likely to allow an inspection to obtain HRMS. Households who had physical damages to their home or experienced a tropical storm/hurricane are more likely to demand the risk information (HRMS). A household, whether aware or not of the MSFH program, does not seem to affect the demand for risk mitigation information. Households who had damages and experience with storms, who live in an evacuation zone are seen to feel venerable. Households who, are also living in Florida longer, are certain that they have necessary information and have a plan to act on, feel less vulnerable. Households who have insurance, information and a plan to act on are more likely to be aware of the MSFH program. There is limited evidence that households with low income and less education tend to have a higher demand for risk information. Thus, more aggressive targeting to reach low income and less educated households will increase the programs' effectiveness. Households with more members living in the home are less likely to demand risk information. Households who live in a manufactured or mobile home are less likely to allow inspection though they are more likely to be aware of the MSFH program. These groups of households that face a disproportionately higher level of risk should be a focus of priority in the future.

Accessible risk information is often missing in the context of natural hazards mitigation planning. An essential component of the MSFH program is to provide homeowners with risk information to facilitate risk mitigation activities. A wide range of literature, documents that mitigation measures adopted by households are sensitive to useful risk information available. Information sensitive proactive mitigation measures are very efficient from the viewpoint of economic returns (Multihazard Mitigation Council

2005). The indirect benefits not only include reduced public expenditures in post-disaster recovery process, but it helps to stabilize insurance premiums at relatively low levels, as it is likely to reduce the extent of catastrophic losses.

Looking back, in 1968 the federal government instituted the National Flood Insurance Program (NFIP) task force, which suggested that the application of the NFIP could improve the economic efficiency of flood plain households, and that "property owners must have sufficient information about flood risk... to make well-informed home purchase decisions" (Krutilla 1966). The same argument holds for promoting hurricane preparedness culture through mitigation measures since the information regarding HRMS can be used in setting property values, which is reflective of mitigation measure undertaken to withstand the rising threat of coastal hazards.

The results also point resilience, adaption, or salience nature of human nature. Duration of residency in Florida (*Residency*) reduces feeling of vulnerability, and also inspection willingness of households. Florida is known for its wild hurricane season (Jewell 2002); and longer a household resides in Florida, it can possibly signal experience of the household with hurricanes. Therefore, with repeated encounters with hurricanes and with developed resilience to hurricane damages, households are not willing to seek risk information. If a household does not feel vulnerable, even after encountering hurricanes or after experiencing hurricane damages in the past, it is less probable that the household seek risk information or a MSFH inspection visit (see Table 15). It is therefore important to incorporate policy prescription that targets resilience to hurricane damages, and result efficient mitigation investment through risk information.

In closing, I find robust evidence that a household is more likely to allow inspection to seek risk information, if the household has a insurance, feels vulnerable, had storm related damages in the past, or exposed to storms before. The findings indicate the MSFH program's unique ability to link incentives offered by private (insurance companies) and public agencies (State) in promoting mitigation for vulnerable groups of households. However, consideration should be given to set priorities, and target households who face a disproportionately higher risk but still less likely to respond (e.g. large households and mobile home residents). While combining different set of incentives can be very effective to establish private–public partnership (Gutmann 2006) in co-producing the optimal level of mitigation for the society, attention should be given to ensure that one set of incentives complements the other, rather than undermining each other.

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TABLES

Table 8: General findings from survey responses

Survey Question	N	%
A. How vulnerable do you feel to damages from a hurricane or related tornado or flooding hazards?		
Extremely Vulnerable	99	12.38 %
Somewhat Vulnerable	336	42.00 %
Not Too Vulnerable	338	42.25 %
Not Sure	27	3.37 %
Total	800	100.00%
B. Have you or any adults in your household been living in a home physically damaged by a hurricane?		
Yes	317	39.62 %
No	483	60.38 %
Total	800	100.00 %
C. How badly was it damaged?		
Major	59	18.61 %
Moderate	120	37.85 %
Slight	138	43.53 %
Total	317	100.00 %
D. What were the primary causes of damages to your home		
Wind Debris Breaking Windows	56	17.83 %
Wind Damaging to the Roof	195	62.1 %
Flooding Related to Hurricane Inundation	17	5.41 %
Trees Falling on House	31	9.87 %
Something Else	13	4.14 %
Do Not Know	2	0.64 %
Total	314	100.00 %

Survey Question	N	%
E. Are you aware of any discounts offered by your insurance company for homes that have hurricane safety features?		
Yes	403	50.38 %
No	347	43.38 %
Do Not Know	47	5.88 %
No Response	3	0.38 %
Total	800	100.00 %
F. Would you allow a State inspector into your home to evaluate hurricane mitigation measures for free?		
Yes	535	66.88 %
No	265	33.12 %
Total	800	100.00 %
G. Are you aware of the Sate program called My Safe Florida Home that provides free home inspections and monetary (grant) assistance for residents to strengthen their homes?		
Yes	235	29.38 %
No	565	70.62 %
Total	800	100.00 %
H. Do you have a plan for what you would do if a serious hurricane threatens your home?		
Yes	692	85.3%
No	118	14.8%
Total	800	100.0%
I. How certain are you that you have all the information to protect yourselves and your home from hurricane damages?		
Not sure	16	2 %
Not certain at all	63	7.88 %
Somewhat certain	253	31.63 %
Very certain	468	58.50 %
Total	800	100 %

Notes: Percentages may not add up to 100% due to rounding of decimals.

Table 9: Definitions and descriptive statistics

Variable	Description	N	Mean	St. Dev
HRMS	Would you allow State inspector into your home to evaluate hurricane mitigation measures for free? (1= Yes, 0= otherwise)	596	0.70	0.46
Vulnerability	How vulnerable do you feel to damages from hurricane or related tornado or flooding hazards? (1= extremely or somewhat vulnerable, 0= not too vulnerable)	596	0.56	0.50
Insurance	Do you currently have homeowner's or renter's insurance? (1= Yes, 0= otherwise)	596	0.88	0.33
Damage	Have you living in a home physically damaged by a hurricane? (1= Yes, 0= otherwise)	596	0.40	0.49
Exposure	Have you experienced any tropical storm or a hurricane? (1= Yes, 0= otherwise)	596	0.96	0.18
Members	How many people live in your household?	596	3.19	5.78
Education	What is the highest grade of school completed by an adult member of your household? (1= elementary grade school, 2= some high school, 3= high school graduate, 4= some college, 5= college graduate, 6= graduate degree)	596	4.55	1.17
Residency	How many years you have been a permanent resident of Florida? (1= <=2 yrs, 2= 3-10 yrs, 3= 11-20 yrs, 4= 21-50 yrs, 5= more than 50 yrs)	596	3.38	1.06
Mobilehome	Type of home (1= manufactured or mobile home, 0= otherwise)	596	0.062	0.24
Income	What is your annual household income? (1= under $20,000, 2= $20,000-30,000, 3=$30,000-50,000, 4= 50,000-75,000, 5=75,000-1,00,000, 6= more than 1,00,000)	596	3.66	1.64
Aware	Are you aware of the Sate program called My Safe Florida Home? (1 if Yes, 0 = otherwise)	596	0.31	0.46
Plan	Do you have a plan if a serious hurricane threatens your home? (1= Yes, 0= otherwise)	596	0.85	0.36
Information	How certain that you have all the information to protect yourselves and your home from hurricane damages? (1= not certain at all, 2= somewhat certain, 3= very certain)	596	2.52	0.64
Dependent	Are you living with children under 12 years and/ or seniors above 65 years? (1= Yes, 0= otherwise)	596	0.55	0.50
Evacuation	Is your home located in a hurricane evacuation zone? (1= Yes, 0= otherwise)	596	0.30	0.46
Gender	Gender (1= if respondent is male, 0= female)	596	0.39	0.49

Table 10: Estimated probability (Probit estimation) of allowing HRMS inspection

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Vulnerability	0.25 (0.11)**	0.25 (0.11)**	0.24 (0.12)**	0.23 (0.12)**
Insurance	0.51 (0.17)***	0.54 (0.18)***	0.56 (0.18)***	0.53 (0.17)***
Damage	0.43 (0.12)***	0.43 (0.12)***	0.44 (0.12)***	0.43 (0.12)***
Exposure	0.63 (0.31)**	0.63 (0.31)**	0.64 (0.31)**	0.63 (0.30)**
Members	-0.03 (0.02)	-0.03 (0.02)*	-0.02 (0.01)**	-0.03 (0.01)**
Education	-0.10 (0.05)*	-0.08 (0.05)	-0.08 (0.05)	-0.09 (0.05)*
Residency	-0.12 (0.05)**	-0.12 (0.06)**	-0.12 (0.06)**	-0.11 (0.06)**
Mobilehome	-0.48 (0.23)**	-0.50 (0.23)**	-0.50 (0.23)**	-0.49 (0.23)**
Income		-0.03 (0.04)	-0.03 (0.04)	
Aware		-0.01 (0.12)	-0.01 (0.12)	-0.02 (0.12)
Plan		0.02 (0.17)	0.04 (0.17)	0.01 (0.17)
Information			-0.06 (0.09)	-0.06 (0.09)
Dependent			-0.08 (0.11)	-0.07 (0.11)
Evacuation				0.09 (0.13)
Gender				0.06 ((0.12)
Constant	0.14 (0.43)	0.12 (0.43)	0.26 (0.46)	0.23 (0.46)
N	596	596	596	596
Pseudo LL	-337.84	-337.60	-337.19	-337.01
Wald (χ^2)	49.14***	50.78***	53.23***	52.44***

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

Table 11: Marginal effects of Probit estimation reported in Table 10

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Vulnerability	0.09 (0.04)**	0.09 (0.04)**	0.08 (0.04)**	0.08 (0.04)**
Insurance	0.19 (0.06)***	0.20 (0.07)***	0.21 (0.07)***	0.20 (0.07)***
Damage	0.14 (0.04)***	0.14 (0.04)***	0.15 (0.04) ***	0.14 (0.04)***
Exposure	0.24 (0.12)**	0.24 (0.12)**	0.24 (0.12) **	0.24 (0.12)**
Members	-0.01 (0.01)	-0.01 (0.005)*	-0.01 (0.004)**	-0.01 (-0.005)*
Education	-0.03 (0.02)*	-0.03 (0.02)	-0.03 (0.02)	-0.03 (0.02)*
Residency	-0.04 (0.02)**	-0.04 (0.02)**	-0.04 (0.02)**	-0.04 (0.02)**
Mobilehome	-0.18 (0.09)**	-0.19 (0.09)**	-0.19 (0.09)**	-0.18 (0.09)**
Income		-0.01 (0.01)	-0.01 (0.01)	
Aware		-0.003 (0.04)	-0.002 (0.04)	-0.01 (0.04)
Plan		0.005 (0.06)	0.01 (0.06)	0.002 (0.06)
Information			-0.02 (0.03)	-0.02 (0.03)
Dependent			-0.03 (0.04)	-0.02 (0.04)
Evacuation				0.03 (0.04)
Gender				0.02 (0.04)
N	596	596	596	596
Pseudo LL	-337.84	-337.60	-337.19	0337.01
Wald (χ^2)	49.14***	50.78***	53.23***	52.44***

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

Table 12: Bivariate Probit estimation of HRMS inspection (*Inspection*) and MSFH program awareness (*Aware*)

Variable (X)	**Model 5**		**Model 6**		**Model 7**		**Model 8**	
	Inspection	*Aware*	*Inspection*	*Aware*	*Inspection*	*Aware*	*Inspection*	*Aware*
Vulnerability	0.25 (0.11)**		0.25 (0.11)**		0.24 (0.12)**		0.23 (0.12)**	
Insurance	0.51 (0.17)***	0.45 (0.19)**	0.54 (0.18)***	0.48 (0.19)***	0.56 (0.17)***	0.43 (0.19)**	0.53 (0.17)***	0.34 (0.19)*
Damage	0.43 (0.12)***	0.12 (0.11)	0.43 (0.12)***		0.44 (0.12)***		0.43 (0.12)***	0.09 (0.11)
Exposure	0.63 (0.31)**		0.63 (0.31)**	0.05 (0.3)	0.64 (0.31)**		0.63 (0.3)**	
Members	-0.03 (0.02)		-0.03 (0.02)*	-0.07 (0.04)	-0.02 (0.01)**	-0.07 (0.04)*	0.03 (0.01)*	
Education	-0.1 (0.05)*		-0.08 (0.05)	0.06 (0.05)	-0.08 (0.05)	0.04 (0.05)	-0.09 (0.05)*	
Residency	-0.12 (0.05)**		-0.12 (0.06)**		-0.12 (0.06)**		-0.11 (0.06)**	0.04 (0.05)
Mobilehome	-0.48 (0.23)**		-0.5 (0.23)**		-0.5 (0.23)**		-0.49 (0.23)**	0.4 (0.23)*
Income			-0.03 (0.04)		-0.03 (0.04)			0.1 (0.04)***
Plan			0.02 (0.17)		0.04 (0.17)		0.01 (0.17)	
Information		0.19 (0.09)**			-0.06 (0.09)	0.19 (0.09)**	-0.06 (0.09)	0.15 (0.09)*
Dependent					-0.08 (0.11)		-0.07 (0.11)	
Evacuation				0.09 (0.12)		0.08 (0.12)	0.09 (0.13)	0.05 (0.12)

Gender							0.06 (0.12)	0.08 (0.11)
Constant	0.14 (0.43)	-1.44 (0.27)***	0.12 (0.43)	-1.06 (0.41)***	0.26 (0.46)	-1.38 (0.33)***	0.24 (0.46)	-1.83 (0.33)***
N	596	596	596	596	596	596	596	596
ρ	-0.01 (0.07)		-0.01 (0.07)		-0.005 (0.07)		-0.01 (0.07)	
Log pseudo - likelihood	-699.43		-699.14		-696.6		-693.18	

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

Table 13: Marginal effects of estimated coefficients reported in Table 12

Variable (X)	Model 5		Model 6		Model 7		Model 8	
	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx
Vulnerability	0.03 (0.01)**	0.06 (0.03)**	0.03 (0.01)**	0.06 (0.03)**	0.02 (0.01)**	0.06 (0.03)**	0.02 (0.01)*	0.05 (0.03)**
Insurance	0.14 (0.04)***	0.05 (0.06)	0.14 (0.03)***	0.06 (0.06)	0.14 (0.03)***	0.07 (0.06)	0.12 (0.03)***	0.07 (0.06)
Damage	0.07 (0.03)**	0.07 (0.04)*	0.04 (0.01)***	0.1 (0.03)***	0.04 (0.01)***	0.1 (0.03)***	0.07 (0.03)**	0.08 (0.04)*
Exposure	0.07 (0.04)*	0.16 (0.08)*	0.08 (0.05)*	0.16 (0.11)	0.07 (0.04)**	0.17 (0.08)**	0.07 (0.04)**	0.17 (0.08)**
Members	-0.003 (0.002)	-0.01 (0.005)	-0.02 (0.01)**	0.01 (0.01)	-0.02 (0.01)**	0.01 (0.01)	-0.003 (0.002)*	-0.01 (0.004)*
Education	-0.01 (0.005)*	-0.02 (0.01)*	0.01 (0.01)	-0.03 (0.02)*	0.002 (0.01)	-0.03 (0.02)*	-0.01 (0.005)*	-0.02 (0.01)*
Residency	-0.01 (0.005)**	-0.03 (0.01)**	-0.01 (0.006)**	-0.03 (0.01)**	-0.01 (0.006)**	-0.03 (0.01)**	-0.001 (0.01)	-0.04 (0.02)**
Mobilehome	-0.05 (0.03)**	0.12 (0.06)*	-0.06 (0.03)**	-0.13 (0.06)**	-0.05 (0.03)**	-0.13 (0.06)**	0.02 (0.07)	-0.21 (0.06)***
Income			-0.003 (0.004)	-0.01 (0.01)	-0.003 (0.004)	-0.01 (0.01)	0.02 (0.01)***	-0.02 (0.01)***
Plan			0.002 (0.02)	0.004 (0.04)	0.004 (0.02)	0.01 (0.04)	0.0007 (0.02)	0.001 (0.04)
Information	0.05 (0.02)**	-0.05 (0.02)**			0.04 (0.02)	-0.06 (0.03)*	0.03 (0.02)	-0.05 (0.03)*
Dependent					-0.01 (0.01)	-0.02 (0.03)	-0.01 (0.01)	-0.02 (0.03)

Evacuation			0.02 (0.03)	-0.02 (0.03)	0.02 (0.03)	-0.02 (0.03)	0.02 (0.03)	0.01 (0.04)
Gender							0.03 (0.03)	-0.01 (0.04)
N	596	596	596	596	596	596	596	596

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

$Y_{11} = P(HRMS = 1, Vu\ln erability = 1)$ and $Y_{10} = P(HRMS = 1, Vu\ln erability = 0)$

Table 14: Bivariate Probit estimation of allowing HRMS inspection (*Inspection*) and vulnerability (*Vulnerability*)

Variable (X)	**Model 9**		**Model 10**		**Model 11**		**Model 12**	
	Inspection	*Vulnerability*	*Inspection*	*Vulnerability*	*Inspection*	*Vulnerability*	*Inspection*	*Vulnerability*
Insurance	0.50 (0.17)***		0.53 (0.18)***		0.56 (0.18)***		0.53 (0.17)***	
Damage	0.47 (0.11)***	0.46 (0.11)***	0.48 (0.12)***	0.48 (0.11)***	0.49 (0.12)***	0.55 (0.11)***	0.48 (0.12)***	0.54 (0.11)***
Exposure	0.7 (0.3)**	0.94 (0.33)***	0.72 (0.3)**	0.98 (0.34)***	0.72 (0.3)**	1.14 (0.35)***	0.72 (0.3)**	1.14 (0.35)***
Members	-0.03 (0.02)		-0.03 (0.02)		-0.02 (0.01)**		-0.03 (0.01)*	
Education	-0.1 (0.05)*		-0.08 (0.05)		-0.08 (0.05)	-0.03 (0.05)	-0.09 (0.05)	
Residency	-0.12 (0.05)**		-0.12 (0.05)**		-0.13 (0.05)**	-0.1 (0.05)**	-0.12 (0.05)**	-0.1 (0.05)*
Mobilehome	-0.47 (0.23)**		-0.49 (0.23)**		-0.49 (0.23)**		-0.48 (0.23)**	0.11 (0.24)
Income			-0.03 (0.04)		-0.03 (0.04)			0.02 (0.03)
Aware			-0.01 (0.12)		-0.01 (0.12)		-0.02 (0.12)	
Plan			-0.01 (0.17)	-0.34 (0.15)**	0.04 (0.17)		0.01 (0.17)	
Information					-0.08 (0.09)	-0.29 (0.09)***	-0.09 (0.09)	-0.31 (0.09)***
Dependent				-0.16 (0.11)	-0.08 (0.11)		-0.07 (0.11)	
Evacuation		0.38 (0.12)***		0.4 (0.12)***		0.41 (0.12)***	0.12 (0.13)	0.41 (0.12)***

Gender						-0.24 (0.11)**	0.04 (0.11)	-0.25 (0.11)**
Constant	0.19 (0.42)	-1.05 (0.32)***	0.19 (0.42)	-0.72 (0.35)**	0.4 (0.45)	0.23 (0.46)	0.34 (0.45)	-0.15 (0.41)
N			596		596		596	
ρ	0.14 (0.07)		0.14 (0.07)		0.14 (0.07)		0.14 (0.07)*	
Log pseudo likelihood	-725.3		-721.61		-711.24		-712.74	

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

Table 15: Marginal effects of estimated coefficients reported in Table 14

Variable (X)	Model 9		Model 10		Model 11		Model 12	
	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx	dY_{11}/dx	dY_{10}/dx
Insurance	0.1 (0.04)***	0.08 (0.03)***	0.1 (0.04)***	0.09 (0.03)***	0.11 (0.03)***	0.09 (0.03)***	0.11 (0.04)***	0.09 (0.03)***
Damage	0.21 (0.04)***	-0.05 (0.03)*	0.22 (0.04)***	-0.06 (0.03)*	0.24 (0.04)***	-0.08 (0.03)**	0.23 (0.04)***	-0.07 (0.03)**
Exposure	0.31 (0.06)***	-0.04 (0.1)	0.32 (0.06)***	-0.04 (0.11)	0.34 (0.05)***	-0.06 (0.1)	0.34 (0.05)***	-0.07 (0.1)
Members	-0.005 (0.004)	-0.005 (0.003)	-0.005 (0.003)	-0.004 (0.003)	-0.004 (0.002)**	0.004 (0.002)**	-0.005 (0.003)*	-0.004 (0.002)*
Education	-0.02 (0.01)*	-0.01 (0.003)*	-0.01 (0.01)	-0.01 (0.01)	-0.02 (0.02)	-0.006 (0.01)	-0.02 (0.01)*	-0.01 (0.01)*
Residency	-0.02 (0.01)**	-0.02 (0.01)**	0.02 (0.01)**	-0.02 (0.01)**	-0.05 (0.02)***	0.008 (0.02)	-0.05 (0.02)***	0.01 (0.02)
Mobilehome	-0.09 (0.05)*	-0.08 (0.04)**	-0.1 (0.05)*	-0.08 (0.04)**	-0.1 (0.05)*	-0.08 (0.04)**	-0.07 (0.08)	-0.1 (0.06)*
Income			-0.005 (0.01)	-0.004 (0.01)	-0.006 (0.008)	-0.005 (0.007)	0.01 (0.01)	-0.01 (0.01)
Aware			-0.001 (0.02)	-0.001 (0.02)	-0.001 (0.02)	-0.001 (0.02)	0.003 (0.02)	-0.003 (0.02)
Plan			-0.09 (0.05)*	0.09 (0.04)	-0.01 (0.03)	0.006 (0.03)	0.001 (0.03)	0.001 (0.03)
Information					-0.1 (0.02)***	0.07 (0.03)**	-0.1 (0.03)***	0.07 (0.03)***
Dependent			-0.04 (0.03)	0.04 (0.03)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)

Evacuation	0.1 (0.03)***	-0.1 (0.03)***	0.11 (0.03)***	-0.11 (0.03)***	0.11 (0.03)***	-0.11 (0.03)***	0.13 (0.04)***	-0.09 (0.03)***
Gender					-0.07 (0.03)**	-0.07 (0.03)**	-0.06 (0.04)	0.08 (0.03)**
N	596	596	596	596	596	596	596	596

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis are robust standard errors.

$Y_{11} = P(HRMS = 1, Vu\ln erability = 1)$ and $Y_{10} = P(HRMS = 1, Vu\ln erability = 0)$

CHAPTER IV:

HURRICANE WILMA, UTILITY DISRUPTION AND HOUSEHOLD WELLBEING

1. INTRODUCTION

On 15th October 2005 a tropical depression formed in the Caribbean Sea near Jamaica. Soon it started to intensify and formed a tropical storm. The storm continued intensifying and became a hurricane on October 18. Afterwards it was named Hurricane Wilma. In next 24 hours, Hurricane Wilma turned into a category 5 hurricane with winds of 185 mph (295 km/h). It made several landfalls and the most destructive effects were felt in the Yucatán Peninsula of Mexico, Cuba, and the U.S. state of Florida. At least 63 deaths were reported, and damages were estimated at over $28.9 billion ($20.6 billion in the US; 2005 US dollars). Due to its severe destruction, Hurricane Wilma is among the top five costliest hurricanes ever recorded in the Atlantic (Pasch et al. 2006). The storm whacked the backbone of the Florida Power and Light's (FPL) electrical grid. Almost 3.2 million of FPL's 4.3 million customers were without power (Johnson 2006). The inflicted damage by Wilma on FPL's electrical grid was mainly severe in most populated counties of South Florida, i.e. Broward, Miami-Dade and Palm Beach (Collier et al. 2008).

Supply of drinking water also became limited. Due to loss of power, water stations were unable to operate their pumps properly. Power-loss also reduces water-pressure in pipelines. The water-pressure in pipelines ensures that supplied water is free from harmful bacteria. If the pressure is low, health authorities suggest people to boil water before drinking (Nigg 1990). However, due to interruption in power supply and limited availability of gasoline, households could neither purify nor boil supplied water.

Households' wellbeing was significantly affected by disruptions of public utility services and other associated damages in the aftermath of Hurricane Wilma. Two main factors that determine the extent of loss in household wellbeing are mitigation efforts to reduce wind-related damages and access to alternative options for public utility services. Allocation of additional resources by investing in disaster preparations (e.g. shutters, hurricane resistant windows and doors) reduces damages to certain extent, but cannot mitigate them completely. Money spent on alternative options for recovery, for example by reducing dependence on public utility services (e.g. owning a generator) or by purchasing sufficient hurricane supplies can significantly reduce post-hurricane sufferings. However, as resources are limited, mitigation and alternative recovery measures need to be taken according to their effectiveness. The effectiveness of mitigation measures can provide key inputs for disaster planning (Shafran 2008). Sharing knowledge and experiences with catastrophic incidents also help people to learn the benefit of disaster preparation (Jaeger et al. 2007). Proactive policies can communicate the benefits of mitigation and expedite disaster recovery for citizens exposed to disasters (Kellenberg and Mobarak 2008). To extend this line of research, we investigate the benefit of disaster preparation in the aftermath of Hurricane Wilma.

Researchers at the International Hurricane Research Center (IHRC) in Miami, Florida, conducted a telephone survey immediately after the landfall of Hurricane Wilma (November 13-20, 2005). Selected randomly from a list of registered voters of South Florida, respondents were asked to document their pre-hurricane preparation and post-hurricane experience of damages and loss in utility due to Hurricane Wilma. We have applied a random utility model to analyze their responses. Our findings indicate the importance of electricity and water supply and alternative access to public utility services (e.g. generator). We find investment made on hurricane mitigation significantly improve the economically efficient, and recommend allocation of additional resources in hurricane preparation and recovery services.

2. LITERATURE REVIEW

Low-intensity hurricanes cause less structural damages than high-intensity hurricanes, but still can have severe impact on regional economic activities (Burrus et al. 2002). Local businesses lose substantial amount of economic activities due to hurricanes (Wyman 2006, Toba 2009). Besides financial damages, loss in mental and physical health of survivors raises serious concerns (Chan et al. 2008, Kessler et al. 2008). Hurricane-related post-traumatic stress leads to reduce life expectancy of survivors (Smith 2008). Human sufferings are likely to increase as the average annual hurricane damages are expected to rise in the future (Nordhaus 2006, Banuri 2005). In order to avoid serious consequences, it is important to explore the pathways of how to reduce hurricane related damages and suffering (Hentenryck et al. 2010).

Post-hurricane sufferings are subject to vulnerability, adaptation, or resilience of households. Vulnerability, adaptation, and resilience analyze human dimensions of global environmental change. From Blaikie et al. (1994), vulnerability is a combination of factors that determine the degree to which someone's life and livelihood are at risk by a discrete and identifiable event in nature or in society. Adaptation is generally perceived to include an adjustment in social and ecological systems (Janssen and Ostrom 2006). Resilience determines the ability of one system to absorb changes, damages and discomforts (Holling 1973, Page. 17). An active adaptation to disasters is either intended to reduce losses or alleviate sufferings (Lindell and Whitney 2000). Severe loss in welfare can be also avoided through building inventories that increase resilience to hurricane suffering (Rose 2004). Therefore, scholarly researches are always proposed that explain what kind of mitigation and inventory investment reduces household suffering from catastrophe events (Kunreuther et al. 2004).

People often fail to recognize or act against low-probability but high-consequence events such as hurricanes (Shaw and Woodward 2008). Risk information increases efficiency in managing resources to act against such low-probability and high-consequence events (Costello et al. 1998; Bontems and Thomas 2000). Disaster preparation depends on households' characteristics as well (Peacock et al. 2005). For instance, Peacock (2003) has explained choice of hurricane mitigation measures with year of residency, income and ethnicity. In addition to mitigation measures, evacuation and moving to a shelter are two other important decisions associated with catastrophe events. Evacuation choice of households depends on their risk perception, disaster preparedness, social influence and economic resources (Riad and Norris 1998). Transportation issues or traffic problems associated with evacuation during hurricanes is one of the major factor of concerns (Dow and Cutter 2002). Improved decision support system during hurricane emergencies can therefore facilitate evacuation (Lindell et al. 2005; West and Lenze 1994).

Nevertheless, the literature is limited in evidence that explains how loss in welfare due to hurricane damages reduces, from empirical examples (Ewing et al. 2007). Restoration of utility services, disrupted during catastrophic incidents, is as important as mitigation investments (Carlsson and Martinsson 2008) and efficient allocation of existing resources is possible by investigating households' preference for alternative recovery of utility services and examples of mitigation benefit (Rose 2007). Such findings will guide to better disaster preparations that reduce loss in household wellbeing due to catastrophe damages (Tierney et al 2001).

3. ANALYTICAL FRAMEWORK

Let us suppose that the utility of an individual depends on his consumption of a composite good (G) and essential public utility services (S). That is,

$$U = U(G, S, X) \tag{1}$$

In the above equation, X is the socio-demographic characteristic vector of the respondent. If P represents the price of G and Y is family income, the money-metric representation of utility is,

$$V = V(P, Y, S, X) \tag{2}$$

Now, suppose that a catastrophic event causes interruption in utility services from S_0 to S_1 ($S_0 > S_1$) and CV_S is the corresponding Hicksian compensating variation. Such an interruption results loss in utility. However, by the definition of the Hicksian compensating variation

$$V(P, Y, S_0, X) = V(P, Y + CV_S, S_H, X) \tag{3}$$

CV_S is increasing in ΔS (= S_0 - S_1) and zero as $S_0 = S_1$.

Now, suppose that a hurricane causes monetary damage of D_H and limited supply of utility services, S_H ($S_0 > S_H$). Then, the money metric utility level of the representative respondent is

$$V_H = V(P, Y - D_H, S_H, X) \tag{4}$$

Therefore, the loss in household's wellbeing (ΔV) due to a hurricane is,

$$\Delta V = V(P, Y, S_0, X) - V(P, Y - D_H, S_H, X) \quad (5)$$

In accordance with above discussion, we can empirically test the following three hypotheses.

Hypothesis 1: $\Delta V/\Delta D_H = +$ (higher damage leads to increase the loss of household wellbeing)

Hypothesis 2: $\Delta V/\Delta S = +$ (longer disruption of utility services leads to increase the loss of household wellbeing)

Hypothesis 3: $\Delta V/\Delta X = +/-$ (socio-demographic characteristics of a respondent may either moderate or intensify the loss of household wellbeing)

4. ESTIMATION

Soon after the landfall of Hurricane Wilma (October 24, 2005), researchers at the International Hurricane Research Center (Miami, Florida) conducted a telephone survey (November 13-20, 2005). Respondents were randomly selected from a list of registered voters from three counties of South Florida, i.e., Miami-Dade, Broward and Palm Beach. Out of 612 households surveyed, 39% were from Miami-Dade, 33.7% were from Broward and 27.3% were from West-Palm Beach. However, the total number of usable responses in regression analyses has been reduced to 360 due to missing information. In table 16, we have reported the definitions and descriptive statistics of variables used in the analyses.

Of the usable responses, 40.56% of the respondents are male, 57.22% are White, 18.06% are African-American and 20.28% are Hispanic. Only 10%respondents reported that they evacuated their house due to Hurricane Wilma and only 1.39% went to a hurricane shelter. More than fifty percent (50.42%) of the respondents said that they received free supply of ice, water and food. Approximately 28.33% respondents had access to an electric generator, and 65.56%respondentsused hurricane shutter to protect their homes from strong wind and rain.

Respondents were asked to rank the impact of Hurricane Wilma on their life (*Impact*) in four classes: ‘Devastating’ (*Impact* = 1), ‘Serious’ (*Impact* = 2), ‘Somewhat serious’ (*Impact* = 3) and ‘Not at all serious’ (*Impact* = 4). Almost 17%, 44%, 29% and 11% of the respondents felt that the impact of Hurricane Wilma on their life to be ‘Devastating’, ‘Serious’, ‘Somewhat serious’ and ‘Not at all serious’, respectively. Almost 15% of the respondents said that they never lost power, whereas around 16% of the respondents were without electricity for more than 2 weeks. Water supply of 56.39% of the respondents was never disrupted due to the landfall of Hurricane Wilma. Nevertheless, 14 respondents out of the 360 respondents were without the supply of drinking water for more than 2 weeks. Most of the respondents, 57.50%, had a week stock of hurricane supplies. Nearly 32%, 22%, 11%, 9%, and 27% of the respondents estimated their household cost due to Hurricane Wilma less than \$500, between \$500 and \$1000, between \$1000 and \$2000, between \$2000 and \$3000, and more than \$3000. Nearly 9% and 6% of the respondents said that they were unable to use their telephone and cell phone for more than two weeks.

The explanatory variables in our analysis include: monetary cost of hurricane (D_H ; *Household Cost*, *Wages*), disruption in utility services (ΔS ; *Electricity*, *Water*, *Phone*, *Cell Phone*) and a vector of household characteristics (X) e.g., respondent’s gender (*Gender*), ethnic background (*White, Black, Hispanic*), political orientations (*Democrat,* *Republican*), location (*Miami Dade*, *Broward*, *West Palm*), hurricane preparation (*Shutter, Supplies, Evacuate, Shelter*) and disaster relief (*Ice-Water-Food*).

Given the ordinal nature of the dependent variable, we have applied the ordered logit estimation method (Greene 1995, pp. 469–481). The ordered logit regression is commonly used in similar social science studies (Monge et al. 2011) and the alternative ordered probit specification is only a trivial modification and appears to make no difference in practice (Greene 1997, p. 673). The common empirical specification can be written as follows.

$$\Delta V = \beta_0 + \beta_1 D_H + \beta_2 \Delta S + \beta_3 X + \varepsilon \qquad (6)$$

The above specification can be elaborated that we will estimate using the ordered logistic regression.

$$Impact = \beta_0 + \beta_1\, Household\ Cost + \beta_2\, Electricity + \beta_3\, Water + \beta_4\, Generator + \beta_5\, Supplies + \beta_6\, Ice\text{-}Water\text{-}Food + \beta_7\, Shutter + \beta_8\, Evacuate + \beta_9\, Shelter + \beta_{10}\, Phone + \beta_{11} Cell\ Phone + \beta_{12}\, Wages + \beta_{13}\, Gender + \beta_{14}\, Black + \beta_{15}\, White + \beta_{16}\, Hispanic + \beta_{17}\, Miami\ Dade + \beta_{18}\, West\ Palm + \varepsilon \qquad (7)$$

We used the Broward County as the reference category for location specific dummy variable, and so did not include it in equation (7).

5. RESULTS AND FINDINGS

We have empirically estimated five different specifications of Equation (7). We have reported the proportional odd ratios of corresponding explanatory variables in Table 18. An odd ratio is the probability of an event divided by the probability of that event not occurring. The result suggests that an increase in *Household Cost* causes the odds of a minor hurricane impact to reduce by 0.721 to 0.741 times. In other words, increase in *Household Cost* increases the probability of a major hurricane (*Impact* = 1), significant at

1% level. Interruption in electricity (*Electricity*) and water supply (*Water*) also increase the probability of a major hurricane (*Impact* = 1), at 1% or 5% significance level. As duration of interruption in electricity increases (e.g., from *Electricity* = 1 to *Electricity* = 2), the odd of a minor hurricane impact decreases by 0.861 to 0.871 times. Similarly, the odd of a minor hurricane impact decreases by 0.846 to 0.857 times as water supply gets suspended longer (e.g., from *Water* = 1 to *Water* =2). The odd of a minor hurricane impact increases by 1.425 to 1.471 times in access to an electric generator (*Generator*), although not significant consistently. Other than the third specification, where *Generator* is significant at 1% level, presence of an electric generator reduces increases the odds of a minor hurricane impact only at 15% significance level. It can be seen from Figure 16 that a higher proportion of the respondents without generator report a serious impact of Hurricane Wilma compared to people with access to an electric generator. As we estimate the average expected probability of different values of *Impact* by the fifth specification, the expected probability of *Impact* = 1or 2 is lower for respondents with access to an electric generator compared to those without a generator. No other variable, other than *Household Cost*, *Electricity*, *Water* and *Generator*, determines impact of Hurricane Wilma on the respondent's life significantly.

Table 19 reports the marginal effects of the corresponding odd ratios reported in Table 18. Increase in *Household Cost* raises the probability of a devastating hurricane impact (*Impact* = 1) by 4.6% to 5.6% at 1% level of significance through Model 1 to Model 8. Similarly, the probability of *Impact* = 1 increases by 1.9% to 2.2% with duration of suspension in supply of electricity (*Electricity*) at 5% significance level. Longer suspension of water supply (*Water*) also increases the probability of devastating impact of hurricane (*Impact* = 1) by 1.3% to 2%, at 5% or 1% level of significance. On the other hand, the probability of a devastating impact (*Impact* = 1) reduces by 5.6% to 6.9%, as the household under consideration owns a generator.

We can therefore substantiate the hypotheses mentioned earlier. As proposed in Hypothesis 1, we find evidence that increase in estimated cost of Hurricane Wilma (*Household Cost*) causes major loss in household's wellbeing. In compliance with Hypothesis 2, longer disruption in water (*Water*) and electricity (*Electricity*) supply increases loss in household's wellbeing. A loss in household's wellbeing is also subject to the respondents' characteristic, as proposed in Hypothesis 3. Evidence supports that a respondent suffers less as he installs an electric generator during his hurricane preparation. However, we do not find any significant impact of respondents' gender, ethnic and political orientation, and choice to evaluate and take a shelter during the hurricane, Hurricane Wilma.

6. CONCLUSION

In this study we tried to investigate the impact of hurricane Wilma on household wellbeing and how a wide range factors moderate or intensify this process. It is unusual that the survivors do not realize any significant benefit from hurricane-shutters (***Shutter***). People often do not realize the mitigation benefit, as their expected damages are much lower than actual. Advanced hurricane forecasting and evacuation make hurricanes seem less vulnerable and reduce the expected cost of living in coastal areas (Sadowski and Sutter 2005). We are unable to account expected hurricane damages of the respondents due to data limitation. The limitation may result this insignificant benefit of hurricane-shutters. Still, it can be seen in Figure 17 and 19 that expected probability of reporting devastating or serious impact of Hurricane Wilma (*Impact* = 1 or 2) is higher for respondents without shutter. Future research can explore this issue in greater detail.

None of the socio-demographic characteristics (*Gender*, *Black*, *White*, *Hispanic*, *Democrat*, *Republican* etc.) significantly affects loss in households' wellbeing due to Hurricane Wilma. It represents that post-hurricane suffering of the survivors is somewhat independent of these characteristics. Evacuating the house (*Evacuation*) and/or moving to a shelter (*Shelter*) are also found to be insignificantly affecting the household wellbeing. The hurricane evacuees of South Florida mostly use the long stretch of Interstate 95 (I-95), the main highway on the East Coast of the United States. If the evacuation process is not well coordinated, they may get stranded on the highway in the face of an approaching storm (PBS&J 2002; Dow and Cutter 2002). Inconvenience during evacuation or moving to a shelter (especially with pets, children and elderly) may not be desirable option, which may explain insignificant effect of *Evacuation* and *Shelter*.

Loss in households' wellbeing due to suspension in telecommunication (*Phone*) is also found insignificant. Earlier literature suggests that disruption in telecommunication affects the businesses significantly than households (Bigger et al. 2009). Widely used modern wireless technology of telecommunication is subject to minimal disruption due to hurricanes (Nigg 1990; Acker et al. 2012).

In places like South Florida, coastal residents consider storms as a part of their life (Hallstrom and Smith 2005). Still experience of hurricanes makes them worried (Picou and Martin 2006). Our findings suggest that coastal residents can reduce post-hurricane impacts by having electricity generator as hurricane preparation device. Earlier research also suggests that willingness to pay for alternative power sources increases with more interruption in electricity (Carlsson, Martinsson, and Akay 2011). Given that, a policy recommendation may be subsidizing generator prices for coastal residents to promote more uses.

The empirical evidence indicates that longer disruption in water supply (*Water*) and electricity (*Electricity*) significantly increases loss in household wellbeing. Interruption in supply of electricity makes it difficult to preserve food and affected people are unable to use refrigerator or make ice etc. and the availability of ice, water and food becomes actually important. However, free supply of ice, water and food (*Ice-Water-Food*) seems to make no significant effects on household wellbeing. When hurricane affected people fall short of these basic necessities, they may not wait for free supply of these relief items and so occasional supply of these items may not significantly affect their wellbeing. It may also imply that people are more interested in finding options (e.g. owning a generator) that enable them to cope with these shocks than becoming dependent on limited and occasional supply of hurricane relief products. . Some research suggests that failure in full-cost accounting of coastal disasters in United States results in suboptimal investment in disaster preparation and recovery (Gaddis et al. 2007). Incentivizing specific actions that promotes disaster recovery can mitigate this trend in some extent. Our results also suggest that planning for disaster recovery and rehabilitation may gain by focusing on an enabling agenda that involves participation of community members in a decentralized fashion.

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TABLES

Table 16: Definitions and descriptive statistics

Variable	Definition	N	M	SD
Impact	How would you describe the impact of Hurricane Wilma on your life? (1 = Devastating, 2 = Serious, 3 = Somewhat serious, 4 = Not at all serious)	360	2.34	0.88
Household Cost	How much money do you estimate Hurricane Wilma cost your household? (1 = Less than $500, 2 = $500-$1000, 3 = $1000-$2000, 4 = $2000-$3000, 5 = More than $3000)	360	2.76	1.61
Electricity	How many days was your household without electricity? (0 = Never lost power, 1 = Less than 24 hours, 2 = 3 days or less, 3 = 5 days or less, 4 = 1 week or less, 5 = 10 days or less, 6 = More than 2 weeks)	360	3.34	1.93
Water	How many days was your household without drinkable water? (0 = Never lost water, 1 = Less than 24 hours, 2 = 3 days or less, 3 = 5 days or less, 4 = 1 week or less, 5 = 10 days or less, 6 = 2 weeks or less, 7 = More than 2 weeks)	360	1.30	1.93
Generator	Did you have a generator? (1 = Yes, 0 = No)	360	0.28	0.45
Shutter	Were you able to shutter your home? (1 = Yes, 0 = No)	360	0.66	0.48
Phone	How many days was your household without phone service? (0 = Never lost phone, 1 = Less than 24 hours, 2 = 3 days or less, 3 = 5 days or less, 4 = 1 week or less, 5 = 10 days or less, 6 = 2 weeks or less, 7 = More than 2 weeks)	360	2.74	2.16
Cell Phone	How many days was your household without cellphone service? (0 = Less than 24 hours, 1 = 3 days or less, 2 = 5 days or less, 3 = 1 week or less, 4 = 10 days or less, 5 = 2 weeks or less, 6 = More than 2 weeks)	360	3.39	1.59
Supplies	How many days of hurricane supplies did you have in preparation? (0= None, 1=Supplies for 1 day, 2= 2 days, 3= 3 days, 4=1 week, 5=More than 1 week)	360	3.50	0.86
Ice-Water-Food	In the aftermath did you receive free ice, water, or food? (1= Yes, 0= No)	360	0.50	0.50

Evacuate	Did you evacuate your home during storm or its aftermath? (1 = Yes, 0= Otherwise)	360	0.10	0.30
Shelter	During Wilma did you go to a shelter? (1 = Yes, 0 = No)	360	0.01	0.12
Wages	How many days of lost wages you had because of Hurricane Wilma? (0 = Did not miss work, 1 = 1 day, 2 = 2 days, 3 = 3 days, 4 = 4 days, 5 = 1 week, 6 = 2 weeks, 7 = Lost job)	360	4.46	2.66
Gender	1 if the respondent is Male, 0 otherwise	360	0.41	0.49
Black	1 if the respondent is Black, 0 otherwise	360	0.18	0.39
White	1 if the respondent is White, 0 otherwise	360	0.57	0.50
Hispanic	1 if the respondent is Hispanic, 0 otherwise	360	0.20	0.40
Miami Dade	1 if from Miami-Dade, 0 otherwise	360	0.39	0.49
Broward	1 if from Broward, 0 otherwise	360	0.33	0.47
West Palm	1 if from West Palm, 0 otherwise	360	0.28	0.45

Note: Due to missing information, total number of usable responses in the regression analysis has been reduced to 360.

Table 17: Ordered Logit Estimation Result (Dependent Variable: *Impact*)

	(1) *Impact*	(2) *Impact*	(3) *Impact*	(4) *Impact*	(5) *Impact*
Household Cost	-0.327***	-0.323***	-0.306***	-0.314***	-0.299***
	(0.0668)	(0.0669)	(0.0677)	(0.0676)	(0.0681)
Electricity	-0.140***	-0.138**	-0.145***	-0.141***	-0.150***
	(0.0540)	(0.0541)	(0.0552)	(0.0545)	(0.0556)
Water	-0.168***	-0.167***	-0.154***	-0.166***	-0.154***
	(0.0559)	(0.0559)	(0.0564)	(0.0560)	(0.0565)
Generator	0.357	0.357	0.386*	0.354	0.367
	(0.231)	(0.231)	(0.234)	(0.232)	(0.234)
Shutters	0.393*	0.401*	0.404*	0.393*	0.387*
	(0.222)	(0.222)	(0.222)	(0.222)	(0.223)
Phone	-0.0872*	-0.0818*	-0.0842*	-0.0797*	-0.0819*
	(0.0476)	(0.0480)	(0.0482)	(0.0483)	(0.0483)
Cell Phone	-0.105	-0.0946	-0.104	-0.0990	-0.106
	(0.0651)	(0.0662)	(0.0669)	(0.0664)	(0.0669)
Supplies	0.101	0.0993	0.0694	0.108	0.0789
	(0.117)	(0.117)	(0.119)	(0.118)	(0.119)
Ice-Water-Food	-0.231	-0.231	-0.190	-0.237	-0.185
	(0.202)	(0.202)	(0.206)	(0.203)	(0.206)

Evacuate	-0.262	-0.284	-0.289	-0.269	-0.285
	(0.337)	(0.338)	(0.340)	(0.342)	(0.343)
Shelter	-1.181	-1.228	-1.204	-1.291	-1.245
	(0.838)	(0.847)	(0.839)	(0.854)	(0.837)
Wages		-0.0348	-0.0306	-0.0370	-0.0314
		(0.0392)	(0.0402)	(0.0399)	(0.0406)
Gender			-0.0302	-0.0178	-0.0395
			(0.210)	(0.208)	(0.210)
Black			0.262		0.200
			(0.543)		(0.551)
White			0.632		0.650
			(0.507)		(0.508)
Hispanic			0.804		0.691
			(0.539)		(0.557)
Miami Dade				0.201	0.223
				(0.242)	(0.263)
West Palm				0.0209	0.00406
				(0.263)	(0.268)
LR ($\chi 2$) Test	60.68***	61.47***	65.75***	62.31***	66.59***
Observations	360	360	360	360	360

Note: The constant terms are suppressed; ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis represent corresponding standard error.

Table 18: Proportional Odds Ratio (Dependent Variable: *Impact*)

	(1) *Impact*	(2) *Impact*	(3) *Impact*	(4) *Impact*	(5) *Impact*
Household Cost	0.721***	0.724***	0.737***	0.730***	0.741***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Electricity	0.869***	0.871**	0.865***	0.869***	0.861***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Water	0.846***	0.847***	0.857***	0.847***	0.857***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Generator	1.429	1.430	1.471*	1.425	1.444
	(0.33)	(0.33)	(0.34)	(0.33)	(0.34)
Shutters	1.481*	1.493*	1.497*	1.481*	1.473*
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Phone	0.917*	0.921*	0.919*	0.923*	0.921*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cell Phone	0.900	0.910	0.901	0.906	0.899
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Supplies	1.106	1.104	1.072	1.114	1.082
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Ice-Water-Food	0.794	0.794	0.827	0.789	0.831
	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)

Evacuate	0.770	0.752	0.749	0.764	0.752
	(0.26)	(0.25)	(0.25)	(0.26)	(0.26)
Shelter	0.307	0.293	0.300	0.275	0.288
	(0.26)	(0.25)	(0.25)	(0.23)	(0.24)
Wages		0.966	0.970	0.964	0.969
		(0.04)	(0.04)	(0.04)	(0.04)
Gender			0.970	0.982	0.961
			(0.20)	(0.20)	(0.20)
Black			1.300		1.222
			(0.71)		(0.67)
White			1.881		1.916
			(0.95)		(0.97)
Hispanic			2.235		1.996
			(1.20)		(1.11)
Miami Dade				1.223	1.249
				(0.30)	(0.33)
West Palm				1.021	1.004
				(0.27)	(0.27)
LR ($\chi 2$) Test	60.68***	61.47***	65.75***	62.31***	66.59***
Observations	360	360	360	360	360

Note: The constant terms are suppressed; ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis represent corresponding standard error.

Table 19: Marginal Effects on the Probability of Devastating Impact (*Impact* =1)

	(1)	(2)	(3)	(4)	(5)
	Impact	*Impact*	*Impact*	*Impact*	*Impact*
Household Cost	0.040***	0.039***	0.037***	0.038***	0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Electricity	0.017***	0.017**	0.017***	0.017***	0.018***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Water	0.020***	0.020***	0.019***	0.020***	0.018***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Generator	-0.041	-0.041	-0.044*	-0.042	-0.042
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Shutters	-0.050*	-0.051*	-0.051*	-0.050*	-0.048*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Phone	0.011*	0.010*	0.010*	0.010*	0.010*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Cell Phone	0.013	0.011	0.012	0.012	0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Supplies	-0.012	-0.012	-0.008	-0.013	-0.009
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ice-Water-Food	0.028	0.028	0.023	0.029	0.022
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Evacuate	0.034	0.037	0.038	0.035	0.037
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Shelter	0.206	0.217	0.209	0.231	0.218
	(0.19)	(0.19)	(0.19)	(0.20)	(0.19)
Wages		0.004	0.004	0.004	0.004
		(0.00)	(0.00)	(0.00)	(0.00)
Gender			0.004	0.002	0.005
			(0.03)	(0.03)	(0.03)
Black			-0.030		-0.023
			(0.06)		(0.06)
White			-0.079		-0.081
			(0.07)		(0.07)
Hispanic			-0.081		-0.071
			(0.05)		(0.05)
Miami Dade				-0.024	-0.026
				(0.03)	(0.03)
West Palm				-0.003	-0.000
				(0.03)	(0.03)
LR (χ2) Test	60.68***	61.47***	65.75***	62.31***	66.59***
Observations	360	360	360	360	360

Note: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in the parenthesis represent corresponding standard error.

FIGURES

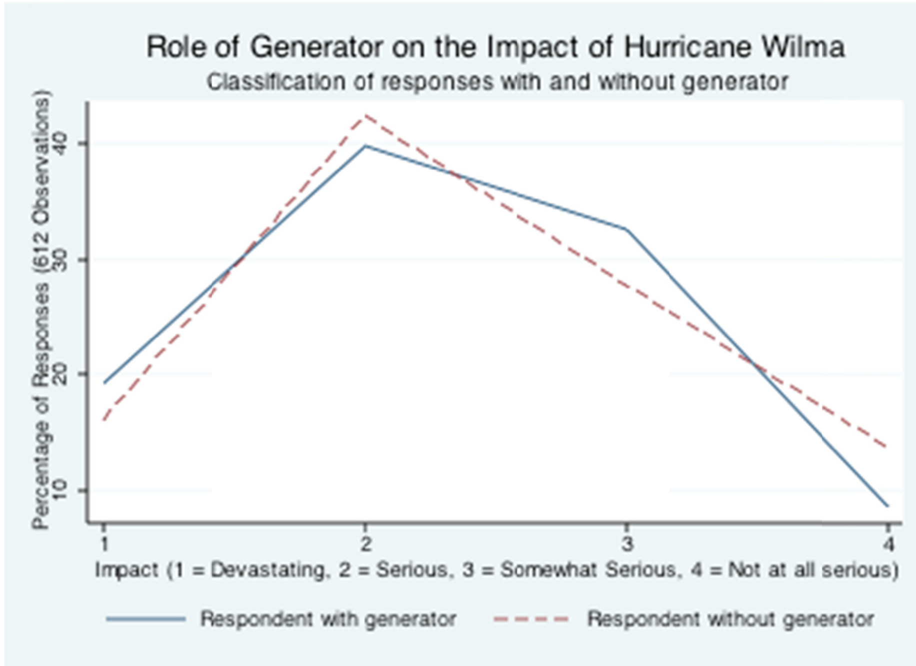

Figure 16: Percentage of impact categories with and without generator

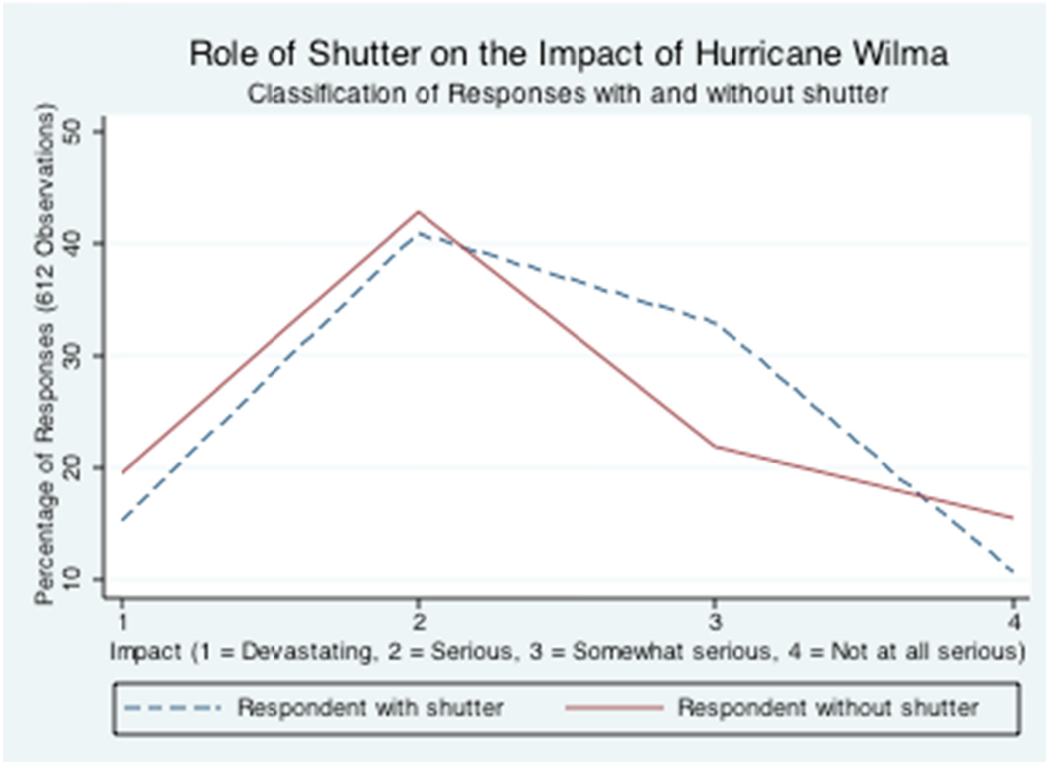

Figure 17: Percentage of impact categories with and without shutter

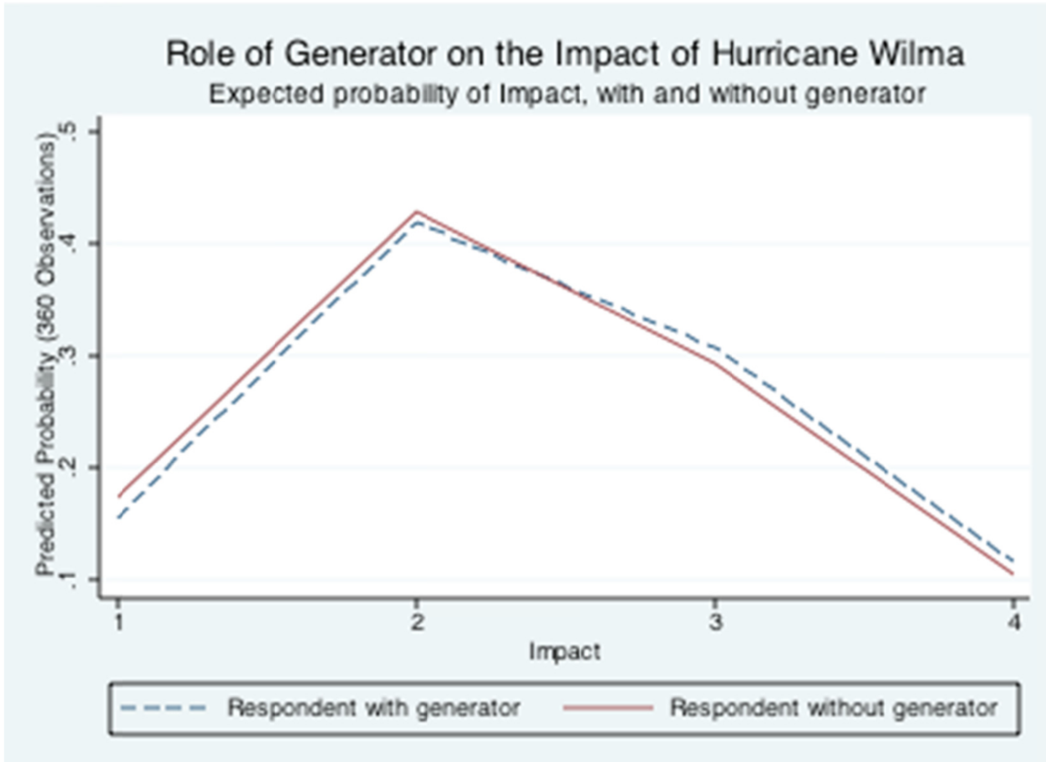

Figure 18: Expected probability of *Impact* =1 **(**Devastating) depending on respondent has generator or not (Model 5)

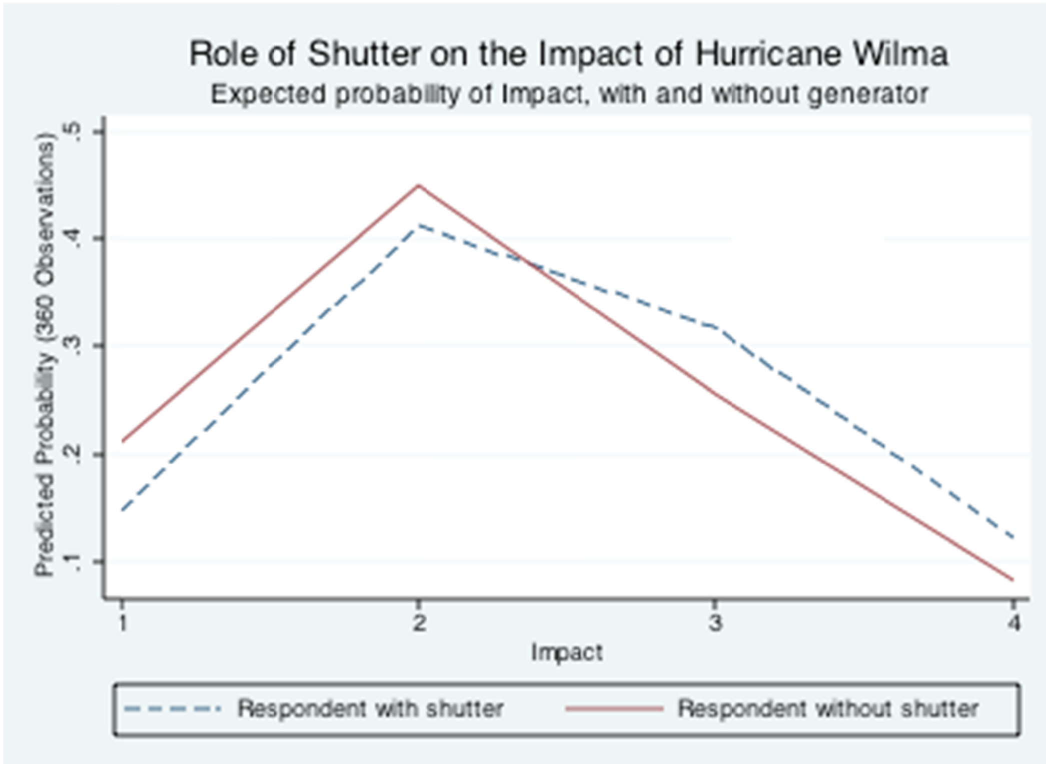

Figure 19: Expected probability of *Impact* = 1 (Devastating) depending on respondent uses shutter or not (Model 5)

VITA

CHIRADIP CHATTERJEE

EDUCATION

2013	**Ph.D. Economics, Candidate** Florida International University (Expected)
2009	**M.A. Economics** Florida International University
2005	**M.Sc. Economics** University of Calcutta, India
2003	**B.Sc. Economics** University of Calcutta, India

EMPLOYMENT

2007-2013	**Graduate Teaching Assistant and Instructor** Department of Economics, Florida International University
2006-2007	**Urban Planner** Kharar Municipality, Govt. Of West Bengal, India
2006-2006	**Faculty** Roy's Institute of Competitive Exam, Kolkata, India

TEACHING

Instructor	Intermediate Macroeconomics (ECO 3203) Applied Macroeconomics (ECO3202) Principles of Macroeconomics (ECO 2013) Principles of Microeconomics (ECO2023)
Guest Lecture	Introduction to Environmental Economics (ECP 3302) Applied Macroeconomics (ECO 3202)
Teaching Assistant	Introduction to Environmental Economics (ECP 3302) Development Economics I (ECS 4011) Comparative Economics Systems (ECS 3003) Fundamentals of Graduate Microeconomics (ECO 6112) Econometrics (ECO 4421) Money and Banking (ECO 3223)

ACADEMIC PRESENTATIONS

Chatterjee, Chiradip and Mozumder, Pallab. 2012. **Adoption of Green Technology: A Diffusion and Learning Process of the Consumers**, June 28th to July 2nd 2013, Western Economic Association, 88th Annual Conference, Seattle, Washington.

Chatterjee, Chiradip and Mozumder, Pallab. 2013. **Pollution Tax, Health Insurance, and Information: Policy Treatment to Reduce Energy Consumption**, June 28th to July 2nd 2013, Western Economic Association, 88th Annual Conference, Seattle, Washington.

Chatterjee, Chiradip and Mozumder, Pallab. 2012. **Adoption of Green Technology: A Diffusion and Learning Process of the Consumers**, 18th November 2012, Southern Economic Association, 82nd Annual Meeting, New Orleans, LA.

Chatterjee, Chiradip 2012. **Pollution Tax, Health Insurance, and Information: Policy Treatment to Reduce Energy Consumption**, 9th November 2012, Seminar Series, Florida International University, Miami, FL.

Chatterjee, Chiradip and Mozumder, Pallab. 2012. **Hurricane Wilma, Utility Disruption and Household Wellbeing**, 10th March 2012, Eastern Economic Association, 38th Annual Conference, Boston, MA.

Chatterjee, Chiradip and Mozumder, Pallab. 2011. **Adoption of Green Technology: A Diffusion and Learning Process of the Consumers**, 15th April 2011, Florida International University, Miami, FL.

PROJECT MANAGEMENT

Coordinated all aspects of a laboratory decision-making experiment of energy conservation. Designed survey, recruited participants, ran experimental sessions, paid respondents and took account of their payments, and analysed their responses. (Role: Researcher)

Coordinated all aspects of a field data collection. Developed the research motive, designed survey, recruited and surveyed respondents, paid respondents, and took account of their payments, and analysed the responses. (Role: Researcher)

Coordinated all aspects of a two-day Graduate Student Association conference at Florida International University. Scheduled speakers and organized discussion groups. (Role: Event Coordinator)

Coordinated all aspects of multiple meetings among populace of Kharar Municipality, India. All meetings were held under the Community Participation Program of Draft Development Plan. Send invitation, organized and harmonized discussion groups, kept account of all payments made on arrangement. (Role: Urban Planner)